

Development of an Internet of Things-Based Carbon Footprint Tracking System for Demand-Side Energy Management

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Abstract: The increase in global warming has been attributed to the increasing emission of anthropogenic greenhouse gases, particularly carbon dioxide (CO₂). The upward trajectory of CO₂ levels in the atmosphere is unsustainable for the near future, potentially leading to a significant increase in average global temperatures. This can further worsen in the next decade if urgent awareness and actions are not taken. Human activities such as electricity generation and consumption from fossil fuel plants have been the major culprits in this ugly trend. Providing individuals with information and feedback on the environmental impact of their actions in real-time and ubiquitously is crucial. However, effective management requires accurate measurement. This thesis, therefore, focuses on implementing an Internet of Things-based carbon footprint tracking system for demand-side energy management integrating a PZEM-004T-100A IoT module with an ESP 8285 module and an AT Mega 328 Microcontroller. A K-Means unsupervised machine learning algorithm was developed to disaggregate the energy usage into appliance combination clusters. This system can measure the electricity consumption of an average household with an active power consumption of 23.0 kW, energy up to 9999.99 kWh, and the associated carbon footprint. The non-intrusive deployment recorded savings of over 65% for a household with 20 appliances. This solution provides homeowners with the needed feedback and awareness of their actions on the environment. The bottom-up technique provides the needed minutiae and collaborative information for energy efficiency, sustainability, and action to combat climate change (UN SDG 12 and 13).

Keywords: Internet of Things (IoT), Carbon Footprint Tracking, Demand-Side Energy Management, Non-Intrusive Load Monitoring (NILM), K-Means Clustering.

Nomenclature

Abbreviation	Description
IoT	Internet of Things
CF	Carbon Footprint
CO ₂	Carbon Dioxide
GHG	Greenhouse Gas
DSM	Demand-Side Management
NILM	Non-Intrusive Load Monitoring
ILM	Intrusive Load Monitoring
PZEM	Peacefair Energy Monitor
MCU	Microcontroller Unit
EC	Electricity Consumption
CED	Carbon Emission Density
RFID	Radio Frequency Identification
BIM	Building Information Modeling
GIS	Geographic Information System
SDG	Sustainable Development Goal
LCD	Liquid Crystal Display
CSV	Comma-Separated Values

1. Introduction

Carbon footprint is a term used to describe the total amount of greenhouse gas emissions directly or indirectly caused by a product throughout its life cycle (cradle to grave) or human activities such as production, consumption, and transportation [12][26][45]. These emissions contribute to climate change, which has far-reaching and potentially catastrophic environmental and societal effects [20]. In 2010, energy production accounted for approximately 35% of total anthropogenic (human activities) greenhouse gas (GHG) emissions [2]. The impact of global climate change arising from anthropogenic gas emissions is significant, and it is increasing daily [23][46]. Hence, urgent action is required to tame this trend before it snowballs into an uncontrollable level for the Earth.

Demand-side response, on the other hand, is an effective energy management tool for end users' effective and efficient use of energy. With the growing global concern for climate change, a bottom-up approach to reducing the carbon footprint is crucial for reducing anthropogenic gas emissions [8]. According to the Intergovernmental Panel on Climate Change (IPCC) report, climate change impacts all regions of the globe [24]. The situation will only worsen if actions are not taken to decrease greenhouse gas emissions by 50% in the next decade and improve the capacity to adapt to these changes [23].

Greenhouse gases are known for trapping heat in the Earth's atmosphere, thereby contributing to global warming. Recent reports have shown that the amount of CO₂ in the atmosphere increases with increasing human activity [3][17]. This effect is more pronounced in resource-poor countries and marginalised communities [24]. Efforts have been made globally to promote environmentally responsible behaviours and strategies in individuals over time; this has not shown any significant result in reducing carbon emissions. Policymakers, energy producers, and consumers must collaborate to reduce carbon emissions. However, 6-8% projected economic growth in India and China and 2.5% in the United States may increase carbon emissions [23]. The concentration of CO₂ in the atmosphere has significantly increased and caused a rise in temperature by up to 1.1 °C as of the year 2020, as shown in Fig. 1. This increase in temperature has resulted in the thermal expansion of oceans and has led to a rise in sea levels ranging from 0.4 to 1.0 meters.

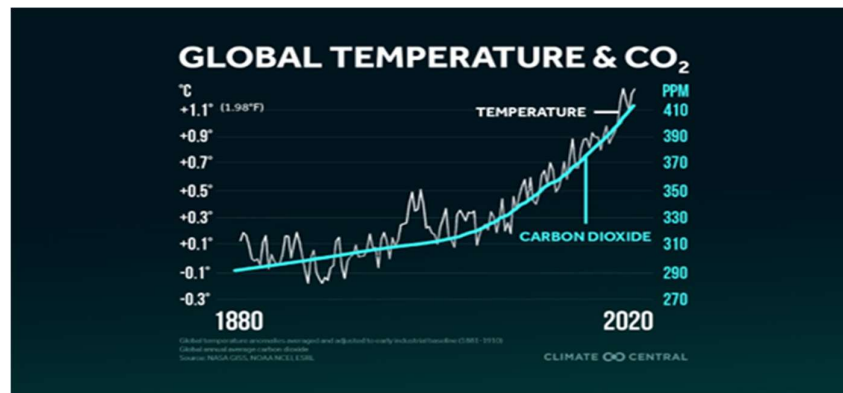


Fig. 1. Global Temperature & CO₂ (Global, 2020)[14]

1.1 Statement of the Research Problem

Carbon dioxide emitted into the atmosphere lasts an average of 50–200 years [16][20]. The upward trend in CO₂ emissions leads to extreme weather conditions such as droughts, heatwaves and flooding. These unfavourable climate conditions have been reported to jeopardise food security and people's livelihoods, with floods and storms displacing more than 20 million annually since 2008 [24]. Climate change has also reduced crop productivity and increased heat-related mortality, heart disease, and mental health issues [24][33][46]. Electricity usage is proven to be a major contributor to greenhouse gas emissions, and tracking it can help individuals reduce their carbon footprint, leading to managing energy efficiently [2][4][21]. There is also a need to increase public awareness and participation in achieving United Nations Sustainable Development Goals (UN SDG) 12 and 13 [44][48]. The increase in average global temperature by 1°C also leads to an increase in the annual peak electricity consumption by 36.1%, leading to more fossil fuel burning and increased carbon emissions from thermal energy sources [23][28]. This vicious cycle must be curtailed before it spirals out of control and becomes an uncontrolled problem. Focusing on individuals and providing them with relevant information about the impact of their activities on climate change can induce small incremental steps that can collectively result in significant environmental effects [37][40]. With the help of IoT technologies, individuals unaware of global environmental protocols can make daily decisions leading to an environmentally sustainable lifestyle [15][42]. This feedback can utilise real-time

collaborative data, historical trends, and averages of human activities like energy usage[43]. This can be achieved by providing end-users with smart meters with communication capabilities that can progressively enhance the accuracy of policy-making and implementation [40].

One effective way to reduce the global impact of carbon emissions is to manage and reduce electricity waste through an IoT-based carbon footprint tracking system for demand-side energy management. This research aims to undo the vagueness in energy usage information; most people are not aware of how much energy is used for different purposes, what sort of difference to make in their day-to-day behaviour, and what efficiency measures to adopt. Building on the statement of the research problem offers a fresh perspective on the literature review of this thesis.

2. Literature Review

2.1 Fundamentals of the Internet of Things

The Internet of Things (IoT) has a long history dating back to machine communication in the 1800s [34]. It allows objects to communicate with each other over the Internet using microcontrollers, sensors, and software applications [10][34]. The IoT is supported by embedded systems, radio frequency identification (RFID), wireless networks, and web services [11][27][32]. It is a multidisciplinary field that combines concepts from computer science, engineering, data science, networking, and security to create a connected ecosystem of smart devices [30].

2.2 Greenhouse Gases

Greenhouse gases (GHG) include carbon dioxide, methane, nitrous oxide, water vapour, and other trace gases [5][31][33]. Although some may view greenhouse gases as a problem, the truth is that they benefit humanity. It is all about finding the correct balance. Without greenhouse gases in the atmosphere, water would exist solely as vapour or clouds in the air, and the atmosphere would consist only of oxygen and nitrogen. This would make the planet nearly uninhabitable, and the average ground temperature would be -6 °C (21 °F). Currently, the average ground temperature is 14.5 °C (58.1 °F), whereas before pre-industrial times it was 13.5 °C (56 °F) [31][39]. Unlike water vapour, the amount of CO₂ in the atmosphere is not limited by natural forces but continues to increase due to human activities. Therefore, CO₂ is more important than water vapour in explaining climate change [31][33].

2.3 Sources of Carbon Emission

Table 1 shows the various sources of carbon emissions, with energy production (electricity and heat) accounting for a high percentage of total emissions worldwide [33][38]. This highlighted the importance of energy management due to the effectiveness of demand-side responses in lowering peak energy demand.

Table 1. Sources of Carbon Emission

S/N	DESCRIPTION	PERCENTAGE
1	Energy Production (electricity and heat)	30-40%
2	Transportation	20-25%
3	Industry	20%
4	Deforestation and Land Use Changes	10-15%
5	Buildings	8-12%
6	Agriculture	10%

Source: (Hannah, 2020 [17]; IEA, 2021 [22]; Kelly et al., 2022 [24]; Pandey et al., 2011 [33])

2.4 Energy Management

Monitoring electricity usage is crucial in reducing greenhouse gas emissions and managing energy efficiently, which ultimately helps individuals minimise their carbon footprint [7][9][27][29][34]. Home energy meters measure the electricity consumption of the entire house. They are usually installed on the primary electrical panel to monitor the overall electrical usage of the home. These meters can offer up-to-date details on electricity consumption and historical data in kilowatt-hours (kWh) [30].

Individuals can reduce their energy consumption and carbon footprint by monitoring their electricity usage patterns. In 2010, energy production accounted for approximately 35% of all human-caused greenhouse gas (GHG) emissions [2]. India's energy, manufacturing, and transportation sectors account for 77% of all emissions [10]. Equation 2.1 provides a mathematical model for calculating the carbon footprint from electricity consumption.

$$\text{Carbon Footprint} = \text{Energy Consumption} \times \text{Carbon Intensity} \quad (1)$$

Where:

Carbon Footprint is measured in kg-CO₂eq

Energy consumption is measured in kWh, and

Carbon intensity is measured in kg-CO₂eq/kWh

The household sector is responsible for a significant proportion of energy consumption and carbon emissions worldwide [29]. In the UK, the residential sector (excluding transport) alone accounts for approximately 30% of all carbon emissions owing to high household energy consumption [4][45]. Similarly, in China, approximately 26% of the total household energy consumption and 30% of CO₂ emissions are attributed to lifestyle and related economic activities [47]. In Greece, household expenditure increased by 44% between 1990 and 2006, with a 60% increase in CO₂ emissions [36]. In India, CO₂ emissions from households also pose a significant concern [4][6][27].

Load monitoring for energy management can be done by non-intrusive load monitoring (NILM) or intrusive load monitoring (ILM). NILM monitors and determines the energy consumption of individual appliances within a household with the installation of the metering device at the service entrance level [19][35]. This allows for predicting which appliances are being used and how much energy they consume at any given time. NILM is a cost-effective and easy-to-install approach compared with Intrusive Load Monitoring (ILM). Unlike ILM, which requires multiple metering devices per room, NILM requires only a single metering device for each energy entrance to the house [25][35].

2.5 Machine Learning

Machine learning is a field of study within artificial intelligence that deals with developing algorithms and models that enable computers to learn and make decisions or predictions without being explicitly programmed [29]. Machine learning algorithms are designed to understand and interpret data, recognise patterns and make predictions or take action based on that data [1]. The electricity usage data and the associated carbon footprint tracking metric can be further analysed for insight, trends and patterns from the historical data using machine learning.

Machine learning algorithms are broadly categorised into supervised and unsupervised learning [25][35].

2.6 Review of Related Works

Many studies have examined CO₂ monitoring and reduction using various approaches. This section discusses a few of these issues.

Alam (2021) [1] examined how the cloud-based Internet of Things can be utilised in smart cities. Information was gathered from citizens, devices, homes, and other sources using IoT sensors. The report highlighted that cloud computing is a game-changing development in internet-based computing. It enables the sharing of ICT resources and communication through a unified network, resulting in a significant boost in the efficiency and performance of IoT. However, the project had limited implementation and scalability due to the power requirements of the on-site devices; there are no standardised methods for measuring the carbon footprint and how IoT applications mitigate carbon emissions.

Gopika and Goerge (2021) [15] investigated rising energy demand due to population growth and industrial expansion. Smart energy meters with IoT devices can help remotely monitor and control energy consumption. Passive infrared (PIR) and PZEM-004T sensors were used to measure voltage and current and post the same to a server. Mobile and web applications allow users to control the systems. The technical knowledge of monitoring and controlling energy consumption related to carbon emission was not provided.

Okedere *et al.* (2021) [31] evaluated Nigeria's various sources of air pollution and the quantity of green gas, which stood at 492.44 million metric tons in 2014, 25% higher than the 1990 value. Energy production, transportation, waste management, land use, and agricultural practices are the primary drivers of pollution. There was no information on emission monitoring, sufficient analysis of energy consumption and the correlation with carbon emissions.

Purwania *et al.* (2020) [34] examined the energy imbalance in Indonesia due to increasing demand and decreasing availability. Poor energy usages harm the environment and worsens global warming and the attending effect. IoT technology can help manage energy use. The article provides an overview of IoT-based energy management progress in Indonesia. Carbon footprint as a metric for energy management was not evaluated from the available data and the implementations were limited to the geography of Indonesia, there was also no sufficient understanding of how technologies influence user behavior and its subsequent impact on carbon emissions.

Bottaccioli *et al.* (2017) [4] deployed a software infrastructure that manages energy patterns in a building. This information can be used by building managers in real time to further understand energy

consumption and temperature trends using IoT devices with meteorological services, building information modelling (BIM), and geographic information system (GIS) technologies. The proposed solution aims to reduce greenhouse emissions and limit climate change for a sustainable society. Smart meters and non-intrusive load monitoring (NIALM) techniques were used for central data collection and breakdown of individual appliance energy consumption. However, the potential impact of such technologies on reducing energy consumption, greenhouse emissions, and climate change was not explored.

West *et al.* (2016) [44] discussed the development of a carbon footprint calculator called 'REAP Petite' that allows users to compare their impact with others in their community and receive recommendations on reducing their carbon footprint. It recommended the creation of additional carbon footprint tools that use bottom-up methods and enable users to compare their results with others. The report emphasised that households account for 60% of territorial emissions in the UK, and taking steps to reduce emissions can help achieve greenhouse gas reduction targets. The study adopts manual input of data. This human input is grossly inadequate to address the needed solution to mitigating carbon footprint.

Sprangers (2011) [39] discussed the various approaches universities use to calculate carbon emissions. Namely, Scope 1 includes emissions from university-owned assets; Scope 2 includes purchased heat and electricity, and Scope 3 includes other emissions from university activities. To calculate the CO₂ emissions, activity data and emission factors are necessary as expressed in Equation 2.2.

$$CO_2 \text{ emission} = \text{Activity data (kWh / kg / km / litres)} * \text{Emission factor (CO}_2 \text{ per unit)} \quad (2)$$

Sutaria and Deshmukh (2008) [40] explored passive sensor-based technologies that can assist individuals in making sustainable lifestyle choices. Feedback based on real-time data and historical trends can encourage positive changes. Incorporating distributed sensors into pervasive networks can make data accessible and improve policymaking. Simple energy meters can provide real-time feedback to users about their environmental impact and enable adjustment of energy consumption for a sustainable environment. The report failed to evaluate the effectiveness of sensor-based technologies in promoting sustainable choices.

Wiedmann and Minx (2008) [45] examined the use of "carbon footprint" by the public and academics, providing a scientific definition. It addressed methodological challenges and highlighted different emission sources. The report identified household electricity and fuel burning as significant contributors to United Kingdom (UK) emissions, including indirect school carbon emissions. However, the information gap was not explored to promote more informed decision-making and actions to reduce carbon footprints in these sectors.

2.7 Research Gaps

The literature review shows the following gaps:

- Technology has the potential to significantly impact the effective use of energy, removing vagueness in electricity billing and contributing to a sustainable environment.
- No empirical evaluation of carbon footprint as a metric in energy management which is a viable factor or metric for effective energy management.
- The use of multiple sensors with the power requirement is not sustainable for energy management. There is need for optimal deployment for scalability.
- Constant supply voltage assumption for computation does not give accurate measurement for electricity usage.

This research shall focus on scalable IoT sensors that could be adopted for different emission densities, weather conditions, living standards, cultures, energy mix and industrial advancement levels. The research shall also serve as a reference and update for emission inventory in mitigating strategies and further works on carbon emission reduction. Cost-effectiveness and cloud technology will also be considered in deploying the novel solution; as such, a non-intrusive load monitoring methodology will be adopted. The material and methodology required to bridge the identified gaps are outlined in the next chapter. Equation Chapter 3 Section 1

3. Research Methodology

3.1 Research Methodology Framework

The methodology adopted in designing an IoT architecture considered the functionality and non-functionality criteria of each module and composite component to ensure the system can capture the total load current, distribution supply voltage and frequency with other necessary standards and requirements. Regarding functionality, the data needed for energy monitoring and appliance features (signatures) were

incorporated into the design. The sampling rate and accuracy were also analysed to ensure accurate and efficient delivery of the required information.

Fig. 2 depicts the design methodology framework, which consists of different layers. Each layer is treated as a functional modular unit, with unique design considerations, technologies, and programming techniques to deliver a unified system.

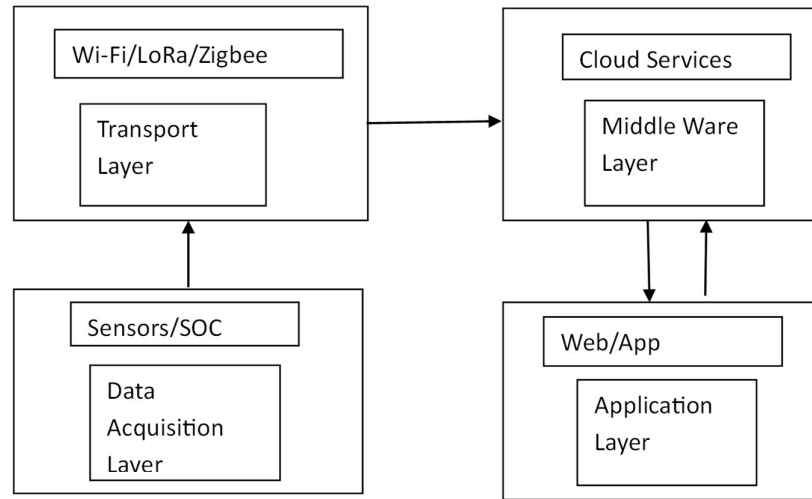


Fig. 2. Methodology Framework

3.2 Data Acquisition Layer

The data acquisition layer as shown in Fig. 2 consists of a PZEM-004T smart IoT sensors module and an AT Mega 328 microcontroller to process data logging and on-site data display. The sensor measures physical quantity like the load (appliance) under transient and steady state, supply voltage from the distribution network, real power, energy, power factor, and the frequency of supply [18], among other things, while the microprocessor processes the acquired data and transmits it to the transport layer.

3.3 Transport Layer

The transport layer consists of an Esp 8285 module for Wi-Fi communication, it serves as the bridge between sensor data and cloud-based computation and data analysis. Its primary function is to transfer the sensor data to the cloud, which can be processed by the cloud-based services and accessed by the user interface. The transport layer utilizes various networks, including wireless (WIFI, Zigbee, LoRa), Mobile networks (3G, 4G & 5G), LAN, Bluetooth, RFID, Fibre, and NFC to facilitate this seamless data transfer. A wireless router with 4G internet access was used for this work.

3.4 Middle Ware Layer (Cloud Computing)

The Internet of Things (IoT) is a vast field encompassing a wide range of unique and adaptable devices. However, these devices often have certain limitations, such as limited storage, power supplies, and performance capabilities, which can hinder the development and scalability of IoT systems. These limitations give rise to complex issues such as compatibility, efficiency, full functionality, and availability. Cloud computing presents a viable and promising solution to circumvent those limitations. The cloud provides shared resources such as networks, storage, computers, and software characterized by ubiquity, low cost, and aesthetic features.

3.5 Application Layer

The application layer facilitates user interaction, device control, and data access. It can be implemented through mobile apps, web interfaces, or dedicated software. In this research, an Android application called Energy & Carbon Footprint Tracker was developed using Firebase Google Cloud infrastructure serving as the integrating platform for deployment.

3.6 Design Analysis

The inventory of the household total active power for 20 appliances using nameplate rating with the supply voltage ranging between 220-260 V was captured and considered for the design. The load ampere and total loads ampere are expressed in Equations 3 and 4 respectively.

$$I = \frac{P}{V} \quad (3)$$

Where:

- I = Load Current (A)
- P = Active Power (W) (or kVA where PF = 1)
- V = Voltage (V)

$$Total\ Load = \sum_{i=1}^N I_i \quad (4)$$

Where:

- N = Total number of appliances and
 - I_i = The load current of appliance ith out of Nth household appliances
- The panel rating is expressed in Equation 3.8.

$$Panel\ rating = Total\ load * 40\% \quad (5)$$

Panel rating is the service entrance rating in ampere and 40% is taken for factors of safety and tolerance for future load growth.

The total load current of the 20 appliances, based on their nameplate ratings, is 44.5 A. Using Equation 5, this results to a required panel rating of 62.3A. Since the PZEM-004T device comes in 10 A and 100 A ratings, the 100 A version (PZEM-004T-100 A) is selected for this work along with the non-functional criteria.

Non-functionality criteria, such as size, cost, and communication capability were also considered. The size of the sensor was carefully considered to ensure that it was compact and could be easily installed in various locations for scalability. Cost was also a key factor in the design process, with affordability and budget constraints being crucial considerations. The communication capability of the sensor was an additional factor that was given special attention to ensure seamless data transfer to the Google Firebase. It was essential that the sensor system could communicate effectively with other devices and systems, considering its compatibility with available communication protocols. In addition, power consumption was also evaluated to ensure that the sensor was energy-efficient and did not require frequent battery replacements.

Fig. 3 illustrates the circuit diagram of the carbon footprint tracking system, which comprises the Pzem-004T-100 A sensor for sensing voltage and load current to measure active power and energy usage. The data is then transmitted to a cloud-based server for further analysis. The AT Mega 328 microcontroller processes the collected data for on-site display and transmits it via the ESP8285 module with integrated Wi-Fi to the Google Firebase server. A mobile app provides a user-friendly interface for accessing the data, enabling the monitoring of trends, history, and patterns for sustainable behaviour.

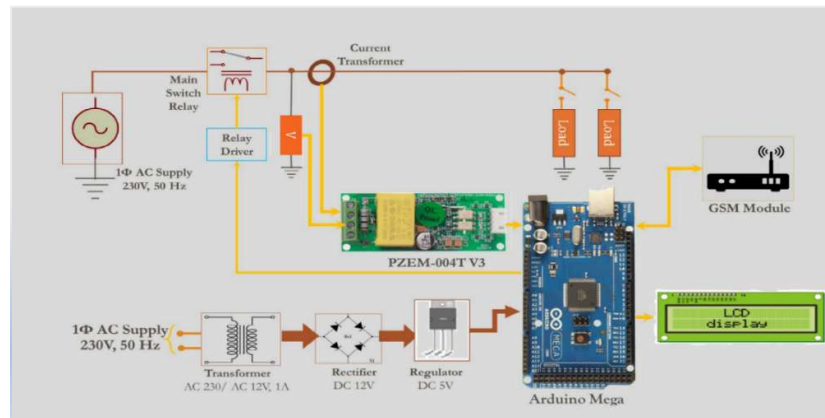


Fig. 3. Circuit of Carbon Footprint Tracking System with Pzem-004T

3.7 Carbon Footprint Tracking Case Study of a Household

A two-bedroom apartment in Minna, Niger State, was considered as a testbed; the device nameplate was used to take the inventory of appliances within the household. This information was used in the design and deployment of the IoT system. Subsequently, the smart meter readings were compared with the nameplate to properly label the appliance features for disaggregation. The smart meter was connected to the service entrance to measure the electricity usage of the appliances. This was achieved by carefully establishing no leakage current on the house's electrical wiring system. Finally, the always-on appliances were restored, and the cloud-based service captured the consumption. The mathematical model expressed in Equation 3.9 was used to evaluate the carbon footprint over a defined timeframe. The CF (kgCO₂) tab represents the calculated carbon footprint, which can be downloaded for further insight and analysis for future comparison and trends. The information can be used for behavioural adjustment towards energy conservation and environmental impact reduction (SDG 12 & 13) goals.

The mobile application development used JavaScript, HTML, CSS, jQuery and Ajax programming languages. JavaScript provides dynamic and interactive functionalities, while HTML defines the structure of the mobile application and CSS defines its presentation. jQuery simplifies JavaScript operations and enables rapid development, while Ajax allows for asynchronous data exchange to enhance user experiences. These technologies are instrumental in creating engaging, responsive, and feature-rich mobile applications.

This allows ubiquitous access to the energy usage data and visualisation for further analysis and insight. Equation 6 gives the carbon footprint resulting from electricity consumption.

$$CF(Kg) = EC(kWh) \times CED(kg / kWh) \quad (6)$$

Where:

CF = Carbon Footprint (Kg)

EC = Electricity Consumed (kWh) and

CED = Carbon Emission Density (kg/kWh).

The carbon emission density for Nigeria's electricity is as 0.402 kgCO₂/kWh [41]. Nigeria's energy mix has been around 80% thermal plant with low renewable energy penetration. The carbon emission density represents the carbon emissions generated by producing one unit (kWh) of electricity [13].

3.8 Energy Usage Pattern

Energy usage data logged into the cloud server is further analysed using a non-intrusive load monitoring methodology to disaggregate the cumulative energy reading into its components. An unsupervised algorithm was applied to depict appliance cluster and energy usage patterns, which could help determine needed action toward a sustainable environment. Energy usage patterns from the aggregate energy data were classified into appliance combination usage and pattern clusters. The K-Means algorithm automatically learns the corresponding appliance-level active power consumption information to identify and attribute energy consumption to specific appliance clusters. The information obtained from this ubiquitous cutting-edge solution can help raise awareness among energy consumers about their carbon footprint and encourage behavioural adjustments towards a more sustainable environment. The integration of the various techniques produced viable results for further discussion.

4. Results and Discussion

4.1 Hardware Implementation

A functional prototype of the Internet of Things (IoT) carbon footprint tracking system was designed and deployed at the service entrance of a household in the Tunga area of Minna, Niger State, as shown in Fig. 4. The IoT prototype comprises PZEM-004T-100 A, Esp 8285, AT Mega 328, and an LCD screen.



Fig. 4. IoT-Based Carbon Footprint Tracking System

The individual component was tested satisfactorily before being interfaced with other components. The PZEM-004T-100 A measures the electrical parameters and responds to requests from the AT Mega 323, which are processed, displayed, and sent to the ESP 8285. The ESP 8285 serves as the Wi-Fi module for cloud services. The household has about 20 appliances with different power ratings and applications. The electrical system in the flat was tested after ensuring that all appliances were switched off. The system's voltage was found to be 248 V, while the frequency was 49.9 Hz. The current and power values were 0.0 A and 0.0 W, respectively. These readings indicated no leakage current in the electrical installation within the flat.

The microcontroller's code was tested and debugged using Arduino IDE to ensure that communication was established between the on-site devices and the cloud services. This enables ubiquitous access and verification of the onscreen display and data logged to the cloud. The IoT module recorded the power consumed by each appliance in its ON state. The data is then collected from the front end and logged into the cloud, providing the household with valuable insights into their appliance's features for further analysis and load disaggregation. By analysing the data, information on appliances contributing to the total household consumption can be identified, and possible adjustments necessary to enhance optimal usage are encouraged. Data taken from the device LCD screen are shown in Table 2. The information depicts the power rating of household appliances under various working conditions. This information is vital in determining the consumption energy cluster.

Table 2. Appliances Audit

SN	Description	Rated Power (W)	Measured Power (W)	Current (A)
1	Haier Thermocool Vacuum kettle	2400	2225.6	9.341
2	Master Chef Deep Fryer 3.5L	2200	2274.7	9.591
3	1.5Hp Haier Thermocool Split AC	1220/1500/3600	1045.1	4.551
4	TV + DSTV	65	55.4	0.261
5	Bulb	10	10	0.071
6	18" Orbit Fan Ceiling Fan	65	61.5	0.331
7	Power Dulux Standing fan	70	48	0.211
8	Haier Thermocool 40" Flat Tv	78	53.3	0.291
9	DSTV		8.8	0.041
10	Phone charger		4.3	0.151
11	Skyrun BCD-118HC Standing Fridge	100	101.8	0.731
12	Skyrun Chest Freezer BD-350C	167	178.6	1.17
13	Washing Machine washing only		200	1.05
14	Washing Machine Spinning only		168	0.721
15	Washing Machine washing + Spinning		249	1.921
16	Lontor Rechargeable fan		12.8	0.121
17	Rechargeable fan High Speed		32	0.261
18	Rechargeable fan Low Speed		3.1	0.041
19	Morphy Richard Vacuum Cleaner 73360	1600/1800	1555	7.106
20	Iron		1053	4.5

A Haier Thermocool Chest Refrigerator screen reading and logging into the cloud services is shown in Fig. 5. This approach was adopted to confirm and check data logged into the cloud services. This process was repeated for the 20 appliances under different operating and steady-state conditions. In those instances, the onscreen values were accurately logged into the Firebase cloud services, where visualisation was carried out for valuable insight and trends in energy usage patterns.



Fig. 5. Onscreen Display: (a) Power and Energy, (b) Voltage and Current

4.2 Mobile App Implementation

The implementation of developed pseudocode code gave rise to a mobile application (Energy/Carbon Footprint Tracker) with an enhanced first and second home screen as depicted in Fig. 6.

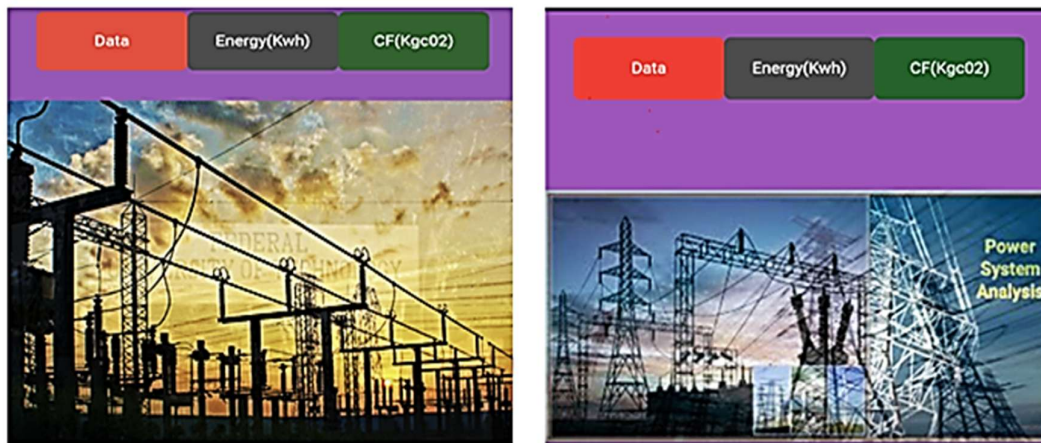


Fig. 6. First and Second Home Screen of the Mobile Application

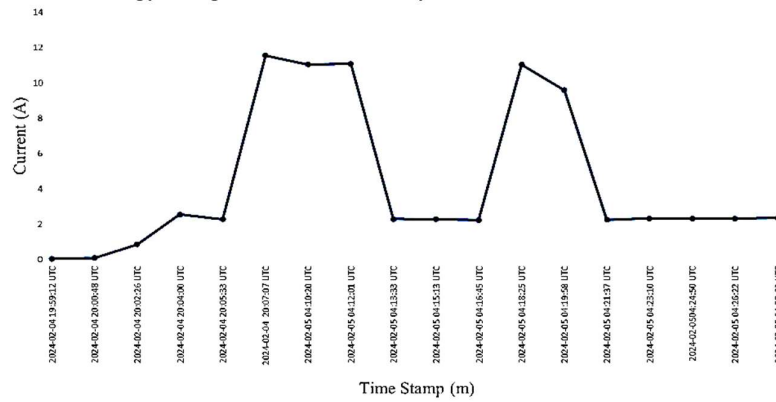
The various tabs on the home screen are used to navigate and interface with electricity usage in kilowatt-hours and carbon footprint in kilograms of CO₂, among other insights and analyses. The data tab is used to update the home appliance database; the chart tab shows the energy disaggregation in a pie chart; the energy tab has the real-time history of energy usage, and the CF (kgCO₂) is the equivalent carbon footprint from electricity usage. This application provides the needed feedback information to the homeowner on their electricity usage, the associated carbon footprint, and energy-saving preferences. The app was able to eliminate human error from manual meter readings and bogus electricity bills at the end of the billing cycle, mostly by the end of the month. The mobile app now makes real-time visualisation of energy usage and trends possible with a user-friendly interface for data visualization options and the option to download data into .csv format for further analysis in MATLAB or the ThingSpeak cloud platform. Finally, the application layer enhanced the user experience, with great potential to promote informed decision-making for attitudinal change and contribute to a sustainable energy system.

Table 3 gives a comprehensive summary of the tracking data, these were accessed via the mobile app interface. The count is the non-null observations, this translates to all columns having 10553 valid values. The mean (average) of the Current is approximately 0.692491 A, the standard deviation of the Energy is approximately 1.556809 kWh and the minimum frequency was recorded as 48.0 Hz.

Table 3. Tracking Data Summary

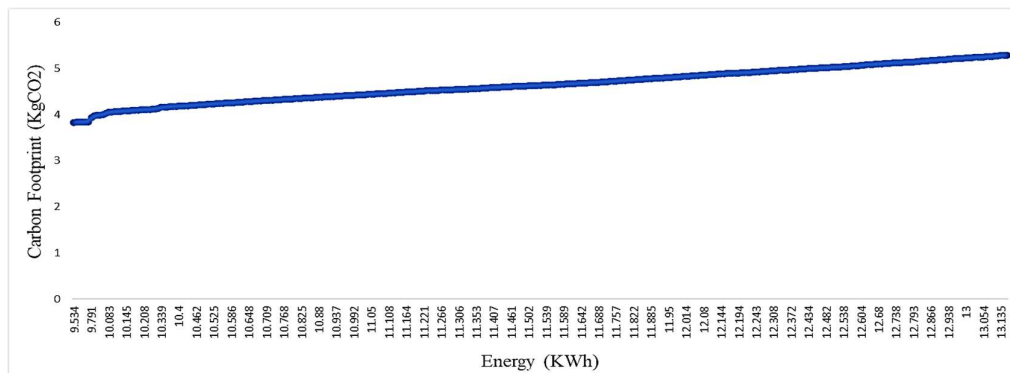
Title	CURRENT(A)	ENERGY (kWh)	FREQUENCY (Hz)	POWER(W)	POWER FACTOR	VOLTAGE (V)	C_F(kgC02)
Count	10553	10553	10553	10553	10553	10553	10553
Mean	0.692	15.872	49.955	142.275	0.861	232.591	6.381
STD	0.554	1.557	0.258	128.546	0.076	4.789	0.626
Min	0.064	13.203	48.000	6.000	0.340	210.400	5.308
25%	0.414	14.490	50.000	84.000	0.850	229.600	5.825
50%	0.463	15.919	50.000	92.000	0.870	234.100	6.400
75%	0.877	16.949	50.000	171.000	0.880	235.700	6.814
Max	3.236	19.696	51.000	750.000	1.000	243.800	7.918

The samples of reading were taken within 15 days, the system accurately captured the energy usage within minutes of usage and logged the value into the cloud server. Fig. 7 depicts the variation in current drawn by the various appliances, this shows the different states of the appliances from on to off and different working states (transient to steady). The depicted figure can be used in feature extraction and a better understanding of the peak and base current demand. The clipping of the peak is an effective demand-side energy management strategy. These could be an adjustment of the thermostat in the fridge and deep freezer to complete the appliance change to an energy-efficient one. The step increase in value also gives an insight into the working mode of appliances within the house which further guides in determining the appliance energy usage and possible adjustment for sustainable behaviour.

**Fig. 7.** Current Demand Over Time

4.3 Carbon Footprint Evaluation

Fig. 8 illustrates a positive correlation between energy consumption and Carbon footprint. As electricity usage increases, the Carbon footprint metric also increases.

**Fig. 8.** Relationship between Energy and Carbon Footprint

The real-time electricity usage data received from the mobile application revealed that 19.696 kWh of energy corresponds to a 7.918 kgCO₂ Carbon footprint. This value can be compared with the average value or per capital value of a nation. This can be used for collaborative or historical trends of their impact on climate change daily, monthly, and yearly. This could also help an individual know if they are eco-friendly or eco-quilt and to better understand their impact on global warming and make informed decisions to mitigate their carbon footprint. By tracking their energy usage and carbon emissions, households can

identify areas where they can reduce their energy consumption, implement energy-efficient practices, and contribute to a more sustainable environment. The data provided by real-time electricity usage tracking is a valuable tool for promoting awareness and encouraging individuals to adopt sustainable behaviours that benefit both the environment and future generations.

4.4 Classification Model

Table 4 depicts the unsupervised K-Means algorithm model developed using Python script with nine clusters of the energy usage patterns for 20 appliances within the household.

Table 4. K-Means Algorithm Model with Nine Cluster

Line	Syntax
i	<code>k_algorithm = KMeans(n_clusters = 9, init='k-means++', n_init= 10, max_iter = 300,</code>
ii	<code>random_state = 111, algorithm= 'elkan')</code>
III	<code>k_algorithm.fit(X1)</code>
IV	<code>labels1 = k_algorithm.labels_</code>
V	<code>centroids1 = k_algorithm.cluster_centers_</code>
VI	<code>y_cluster = k_algorithm.fit_predict(X1)</code>
VII	<code>df['class'] = pd.DataFrame(y_cluster)</code>
VIII	<code>df.head()</code>

The script uses the K-Means clustering algorithm from the sklearn cluster library to cluster the data in X1 into 9 clusters. After fitting the model, it retrieves the labels of each data point and the coordinates of each cluster centre. The labels are used to understand which cluster each data point belongs to, and the cluster centres represent the “average” or “central” point of each cluster. This information provides a better understanding of energy consumption among appliances within each cluster. Fig. 9 demonstrates that 40% of the total energy is consumed by appliances in cluster 0, followed by cluster 6, which constitutes 26% of the energy consumed under the test and evaluation period. This energy reduction of cluster 6 was arrived at after smart adjustments were made in the fridge's thermostat and deep freezer. The clusters showcase the correlation between appliance usage and energy consumption across different settings and operating states.

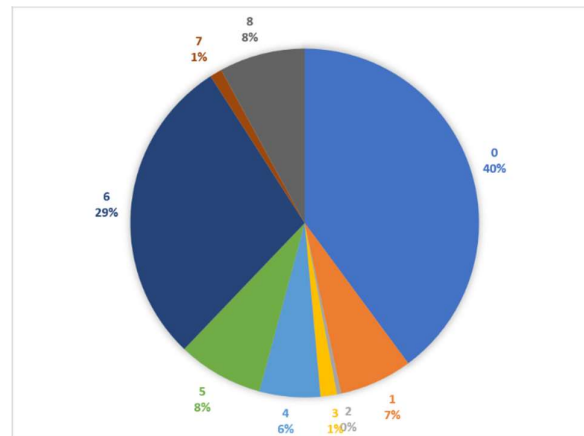


Fig. 9. Load Disaggregation by Cluster

Cluster 0 corresponds to always-on appliances, which account for the largest percentage of energy consumption, 40% of total energy recorded within the duration of test and evaluation. The deep freezer, fridge, fan, and entertainment gadgets constitute the energy demand under cluster 0. This valuable insight can inform meaningful adjustments, such as optimizing the thermostat settings for the fridge and freezer to achieve more efficient energy usage. Replacing the 15 W bulb with a 5 W bulb can further reduce energy consumption, and replacing other inefficient appliances within that cluster can also be considered.

5. Conclusion

The Implementation of an Internet of Things (IoT) based carbon footprint tracking system for demand-side energy management has immense potential to enhance sustainability initiatives and minimise the environmental impact of fossil-burning power plant. With the help of IoT devices and sensors, households

can accurately monitor energy consumption and carbon emissions, empowering them to make informed decisions regarding energy usage optimization. By leveraging real-time visualization and analytics, homeowners can proactively identify areas for improvement, implement energy-saving measures, and prevent potential carbon footprint breaches. The prototype captures electricity usage and carbon footprint by leveraging IoT devices and cloud computing technology. This information is vital for adjusting sustainable electricity usage to create a sustainable environment. Errors arising from human interference, vague idea of how much energy is used, purpose of the usage, lack of information on what sort of differences to make toward a sustainable environment and manual reading of electricity consumption will be resolved with the deployment of this novel idea. K-Means machine learning algorithms deployed via Python enhanced data visualization and analysis by extracting meaningful features from aggregate energy data, leading to more accurate estimates of individual appliance-level energy consumption patterns.

Compliance With Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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