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Research Article

Development of an Edge AI Based Embedded System for Appliance Level Energy Monitoring and management for Smart City- Homes

Banushri.A[1],Kishore Kunal[2], S. Leena Nesamani[3], Vairavel Madeshwaren[4*]
[1]Associate Professor, Department of Computer Science and Engineering,Vistas (Vels Institute of Science, Technology and Advanced Studies) Pallavaram, Chennai, India.
[2]Professor of Business Analytics, Loyola Institute of Business Administration, Chennai, TamilNadu, India
[3]Department of Agriculture engineering, Dhanalakshmi Srinivasan College of Engineering, Coimbatore, TamilNadu, India
[4]Department of Computer Applications, Faculty of Science and Humanities, SRM Institute of Science and Technology, Kattankulathur, Tamil Nadu, India.

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Corresponding mail id: phdannauniv2020@gmail.com

ABSTRACT

With the high increase in the development of the latest tech in modern world, the use of electronic devices and smart appliances has gone way up in the daily life. Consequently, the patterns of energy consumption continuously change, with highly dynamic behaviour over time. Precise monitoring of the real-time loads variation is critical in the grid management process and for the improvement of energy efficiency. Energy disaggregation, which uses the total aggregated load data to estimate the power consumption of individual appliances, is a highly promising and economical method to monitor electricity usage, and in real time. It offers useful information to consumers, utility providers, researchers and policy makers by enabling informed decision making and efficient grid operations implementation strategies. Non- Intrusive Load Monitoring (NILM) is a data-driven method to ascertain the power consumption of individual appliances, based on measurements taken from a single point of measurement (usually a main energy meter). This approach eliminates the need for multiple sensors on each appliance and thus makes it cost-effective and appropriate for smart homes. This thesis is on the design and implementation of an efficient NILM framework based on energy disaggregation methods for residential smart home applications. The proposed research is divided into four major phases. The first phase is a detailed review and comparative analysis of current NILM techniques used with a variety of load characteristics and a focus on their applicability to residential energy monitoring. The development of such techniques will allow for the proper disaggregation of individual appliance loads from aggregated consumption data, which will increase the effectiveness of NILM in the energy disaggregation process. In the second phase, different energy disaggregation algorithms which are suitable for smart home environments are analyzed and the most suitable method for residential load monitoring applications is determined.

Keywords: NILM; appliance-wise power consumption; soft computing approaches; energy disaggregation.

INTRODUCTION

With the increased rate of industrialization in the world, the consumption of electricity has been rising steadily in all sectors. Technological progress has brought a multitude of electrical appliances to everyday life, which has led to increasing dependence on energy-intense appliances for comfortable and convenient life. Consequently, the consumer level energy demand has increased significantly in this fast paced modern society. In response to this growing demand, extensive deliberations have been made in terms of energy conservation and management, demand side management and energy efficient practices. One of the things that can be done to balance the energy demand is changing the consumption behaviour, optimising the schedule of use and adaptation to the energy generation resources. Energy conservation not only assists economic efficiency and demand regulation, but also means that it plays an important role in avoiding carbon emissions.

The Building and Climate Change report underscores the fact that residential and commercial buildings in India are responsible for 39 per cent of the overall carbon emissions, which is more than the emissions from the transportation and industrial sectors (Khan et al., 2025). Further research states that, in countries like India, almost 93 percent of the carbon emissions come from residential buildings (Chen et al., 2019). These findings highlight the need to focus on residential energy efficiency to tackle environmental problems caused by the rapid urbanisation.

The development of smart grid technologies has allowed greater capabilities in power system monitoring and control. Smart metering systems enable consumers to monitor how much electricity they use in a day, and real-time feedback of energy consumption encourages consumers to use their appliances more efficiently. Next-generation smart metering infrastructures enable fine-grained monitoring of load by using new and advanced cloud platforms and intelligent learning algorithms (Lemos et al., 2025). Recent research has shown that real time, appliance level feedback can lead to energy savings of more than 12% (Lin, 2022).

Moreover, real-time identification of loads allows energy providers to provide adequate grid services depending on the usage pattern of consumers. Therefore, online real-time load monitoring systems offer great potential to achieve energy efficiency in terms of better utility support services (Ray, 2025).

The main objective of this research is to achieve efficient Non-Intrusive Load Monitoring (NILM) framework through the use of appropriate energy disaggregation algorithm for smart home applications. The proposed model of NILM is further integrated with a microcontroller based hardware prototype for real-time monitoring and control of appliances towards enhanced energy-efficient operations of the grid (Chen et al., 2021).

Within the modern power networks, the development of smart grid technologies has reinforced the possibilities of data acquisition in real time and load management. Appliance specific usage patterns are an important parameter in the analysis of energy consumption in demand side management applications (Alsalemi et al., 2021).

Load disaggregation or non-intrusive appliance load monitoring is an important source of data for direct feedback control strategies in smart home energy management systems. Existing NILM methodologies can be broadly grouped into intrusive and non-intrusive monitoring methodologies. Intrusive monitoring is the method used to place sensors at the appliance node level, while non-intrusive monitoring uses advanced signal processing and machine learning algorithms to reconstruct individual appliance consumption from the aggregated meter data (Lin et al., 2022).

The framework of NILM improves user awareness of the use of electricity and effective control strategies of devices. The performance of NILM relies on the choice of suitable energy disaggregation algorithms depending on data availability, characteristics of appliances and load profile fluctuations (Joha et al., 2024).

In this study a NILM developments based on a decision tree is developed using benchmark datasets, namely the Reference Energy Disaggregation Dataset (REDD) and the Retrofit Decision Support Tools for UK Homes using Smart Home Technology (REFIT) dataset. A model is proposed which is then tested in terms of the normal performance indicators to prove its effectiveness. Furthermore, in order to validate the experimental results, a microcontroller-based hardware setup which is integrated with the ThingSpeak cloud platform is developed and connected with the proposed NILM model, so as to facilitate real-time monitoring and control of appliances for better energy efficiency (Sayed et al., 2021).

RELATED WORKS

Non-intrusive load monitoring (NILM) has received much attention in academic research and industrial practice during the past two decades, because of its great potential to improve building level energy efficiency (Jahid, 2025). Consequently, significant efforts have been made in developing more robust machine learning models, which constitute a very central role in the energy disaggregation process and are crucial for making energy savings possible. This research trend is basically gone from classical supervised learning methods to deep learning based methods and unsupervised methods such as Hidden Markov Models (HMMs) are still an active research topic because of their performance in the problem of dis-agglomeration (Stogia 2025).

With the constant development of technology, modern electrical appliances become increasingly sophisticated and their operation states become more complex and less distinguishable. In this context, the advent of deep learning is a significant breakthrough in research for energy disaggregation. Three deep neural networks architectures - namely: Long Short-Term Memory (LSTM) networks, denoising autoencoders, and a predictive model for estimating the appliance activation time, deactivation time, and average power consumption (Hu et al., 2020). Their results showed real improvements over the conventional methods in terms of accuracy and adaptability to unseen configurations of houses. Extending this work, proposed a sequence to point learning (Seq2point) framework to deal with the Single-Channel Mix Source Separation (MSS) problem (Yuan et al., 2020). By reformulating the learning task in order to simplify the mapping for the neural nets, their technique achieved better prediction accuracy and better performance on the real-world datasets by the automatic extraction of relevant signal features, which were previously handcrafted.

In accordance with these developments, adaptive CoBiLSTM (Co.-attentive Bidirectional Long Short.-Term Memory) model in order to address the limitations of static disaggregation approaches (Lin 2020). By taking advantage of bidirectional LSTMs, the model captures the context of the variations in consumption patterns and hence gives extra flexibility and accuracy in estimating the appliance. Despite these methodological improvements, NILM still has its own substantial challenges, especially caused by the diversity of appliances and differences in user behavior. Variability prevents development of universally applicable NILM models (Franco et al., 2021). Additionally, the limited temporal resolution of smart meter measurements to limit the performance of disaggregation for some categories of appliances (Gheorghe, 2025).

In order to overcome these limitations, probabilistic methods such as factorial hidden Markov models (FHMMs) have shown great potential. Bonfigli et al. suggested an improved FHMM framework coupled with modified AFAMAP algorithm by exploiting measurements of both active and reactive power for improved accuracy of disaggregation (Lin 2025 et al., 2025). Similarly, Modified FHMM (MFHMM), which decreases the computational complexity while enhancing the segmentation and identification of appliance operating states and demonstrated a good performance on publicly available datasets (Gopinath and Kumar 2023). In parallel, Wu et al. tried to reduce the dependency of HMM-based models on past information about appliances by proposing an adaptive clustering-based approach coupled with FHMMs, which further improved the accuracy in terms of disaggregation (Mari et al., 2023).

Besides probabilistic models, hybrid learning strategies and ways of transfer learning have come out as promising directions. Introducing two transfer-learning strategies which can improve the generalisation of the model and decrease the amount of training data needed (Stefani et al., 2025). A hybrid CNN-LSTM model that takes mutual advantage of spatial and temporal features in load signatures, leading to better accuracy of load disaggregation (Papaioannou et al., 2025).

The question of the scalability and adaptability of NILM solutions is a critical issue in the research. Pereira and Nunes emphasized the need for the design of methods that can be deployed on a large scale in various operating environments (Wang et al., 2022). At the same time there is increasing attention to privacy and ethical issues, for example, the work (Franco et al., 2023) which explored the trade-off between the analytical advantages and the user's privacy in smart-metering systems. Although a lot of progress has been made in the field of NILM research, there are important challenges that remain, in particular with respect to model generalisation and the reliance on labelled training data. These challenges to the optimisation of the whole power distribution network using smart meter data underlining the fact that energy disaggregation is only a part in the bigger picture of energy system efficiency improvement (Serna et al., 2025).

PROPOSED METHOD

The proposed framework works as an intelligent power management system, and thus allows for remote monitoring and control by consumers of electrical appliances in their homes by Internet of Things (IoT) enabled applications such as mobile applications. In conjunction with real time visualization of energy consumption and budgetary management functionalities, the system provides remote as well as manual control (on/off switching mechanisms) of devices. It provides data communication integrity between the user interface and the control unit, includes an emergency alert capability, and integrates a Google Map interface to help utility providers identify the locales with higher than normal energy consumption rates. These features are carefully designed to give consumers as well as the utility operators the ability to move towards sustainable energy practices by allowing ongoing remote monitoring and scheduling of appliance operate, which can optimise energy utilisation.

The hardware structure of the proposed system consists of a client unit as shown in Figure 1. In the present implementation the microcontroller interface i.e. Arduino board is used as the client unit and is responsible for obtaining the measurements from the connected sensors. These measurements are then sent via a central database for storage and further processing. Apart from data acquisition, microcontroller also connects the electrical appliances by controlling them. The central unit is implemented with ESP32 module, with database stored within ESP32 module and web-based services such as monthly energy budgeting and notification alert are delivered.

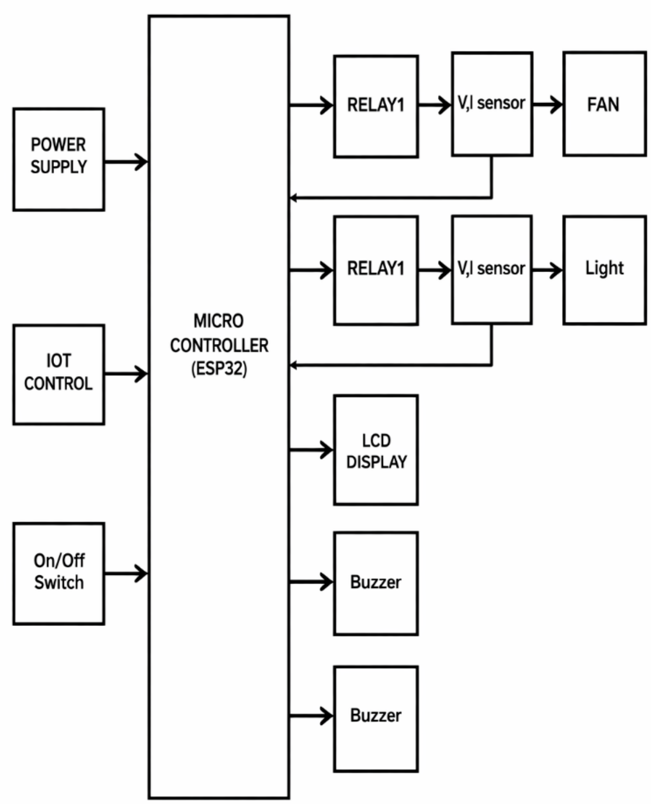

Figure 1: Architecture of the Proposed System Model

Furthermore, the system incorporates a mobile application that is created on a PHP/MySQL stack for IoT-based data monitoring. The application allows the remote access by authorized utility users to a variety of functionalities, consisting of real time visualization of the energy consumption through gauge charts, manual control of appliances, and configuration of system parameters. Concurrently, a web-based interface for end users and utility operators is provided which gives them the opportunity to access, monitor and manage the services provided by the central unit

3.1. SYSTEM ANALYSIS AND DESIGN

In order to build the smart metering system, there are some core entities to be defined, as follows: client, staff, sub-client, power cost, client budget, power consumption records, non-active client contact and system setup. These entities are shown in Figure 1 (System Architecture Diagram) and Entity-Relationship Diagram in figure 2. The relationship between the client and sub-client entities follows a one to many relationship, i.e. one client may contain several sub-clients in a household. Similarly the client table has a one to many relationship with the power cost table - a single power cost record is due to a single client, but a single client can have multiple power cost records over a period of time.

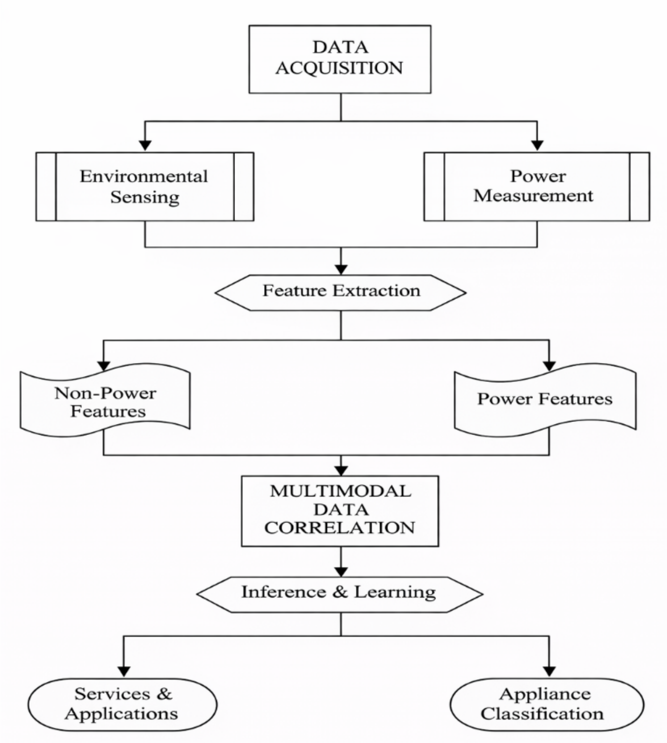

Figure 2: ER Diagram of the Proposed System

The non- active client contact table is committed to save the latest contact details recorded by the service provider. Accordingly, the relation between the client, non-active client contact entities is one to many and is considered to be optional. In addition, the system setup table maintains a one-to-many relationship with the client table, since it is possible to have more than one device configured for one client while, at the same time, each device configuration is only associated with one client. Likewise, the client payment record table is related to the client table in a one to many relationship since payments are done on a monthly basis and each payment record is equal to one client.

In order to distinguish the similar appliances, consecutive Fourier transforms are used to create the spectrograms of the instantaneous power demand. Initially, the discrete time Fourier transform of each signal x is calculated by summation over all temporal indices corresponding to a time less than or equal to tn = 0.5 s by weighting each sample by sinusoids with a frequency of f = 30 kHz. The resulting transform Xj represents the signal in terms of the frequency. A Hanning Window is applied to obtain adequate frequency resolution and to reduce the spectral leakage. windowing configuration is used to specify the overlap (640 samples) between consecutive windows for a segment length (5210 samples). It is noteworthy that this windowing strategy is expected to capture the overarching patterns of the appliances without preferentially biasing transient or steady state behaviour.

$$X(f) = \sum_{n=0}^{N-1} X(n)\, e^{-j2\pi fn}$$

x(n) is the current signal that is measured at discrete times. N is the total number of samples that we consider up to tn = 0.5 s. fff is the frequency component, and its maximum frequency is 30 kHz. X(f) is the frequency domain representation of such a signal.

$$S_{\{xx,j\}} = \frac{2\Delta^2}{T} X_j X_j^*$$

From the visualizations, you can see clear differences between appliances even if you consider only 0.5 seconds of data (15,000 samples). For each appliance we take a slice of 0.5 seconds and add additional zeros to have the same length for each slice. We have chosen this smaller length of time for two main reasons: first, because it allows us to have more training data (from 1876 to 13000 samples), which helps the model to work better; second, because we can now classify appliances in real-time or close to real-time.

3.2 System Modelling

Non-intrusive load monitoring (NILM) is a computational approach for measuring the power consumption of individual appliances using only a single aggregate meter, which measures the consumption of several devices. By using signal processing algorithms in these aggregate observations NILM reduces the need for individual sensor installation on each appliance. Non-intrusive appliance load monitoring (NIALM) is based on the distribution mains where the power signals change and is used to determine the energy consumption of individual appliances. The methodology has many practical uses such as retrofitting appliance recommendations, smart house automation, demand response services, and support for system operators for use in the distribution-level decision making. Every appliance has a unique power consumption signature, allowing the appliance to be identified and analyzed for its behaviour. By taking advantage of these signatures, NILM enables grid management, fault detection and appliance level usage pattern estimation.

The work process of a usual NILM model is shown in Figure 2 and usually consists of five main steps:

- Overall Sensing and data collection Electrical parameters are measured at the sensing nodes at a defined sampling rate.
- Data pre- processing: The collected data are pre - processed to remove noise and redundancy, thereby, ensuring a clean data input for further analysis.
- Feature extraction and classification: The essential features are extracted from the pre - processed data to characterise each load effectively.
- Detection of events: Using the extracted appliance signatures, the model is used to predict the events (OFF, ON or Multi-State) for unseen data samples.
- Model evaluation and validation: The trained model is evaluated on unseen data and the performance metrics such as accuracy, precision, recall, true/false positive rates are evaluated.

3.3. Artificial Intelligence

In general, energy disaggregation algorithms are based on supervised machine learning, a paradigm that requires input samples that have known labels. Machine learning (ML) is a methodology that involves the use of statistical methods to support the progressive improvement in performance of a system through data, an experiential set of data or bio inspired optimization processes. Depending upon the specific mode of learning engaged, ML models are broadly classified into supervised, unsupervised or reinforcement learning. In the field of energy disaggregation, appliance labeling is traditionally carried out with standardized sets of data.

The disaggregation model can include one or more of the following techniques for characterizing the load pattern:

- Classification
- Regression
- Clustering
- Dimensionality Reduction

The selection of the correct technique is dependent on the nature of a dataset and a learning algorithm. Selecting the appropriate classification to perform the task of mapping extracted feature vectors to known appliance signatures is a crucial step to perform in order to accurately identify loads in NILM. Based on the appliance data collected and the corresponding database, appropriate NILM model is developed for effective energy disaggregation.

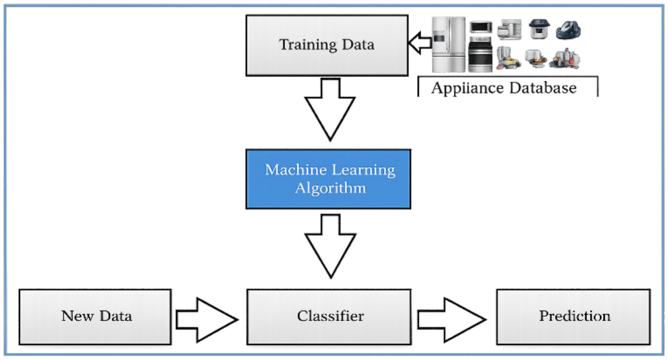

Figure 3: Process of Machine Learning

$$\text{NPV} = \text{t} = \sum_{t=1}^{n} \frac{NCF_t}{(1+i)^t} - \text{I}$$

The resolution of the problem of Non-Intrusive Load Monitoring (NILM) requires the application of machine learning algorithms, which, by their very nature, mediate the complexity of the problem and the refinement of predictive models. The construction of a NILM model is reliant on numerous determinants, including the provision and accessibility of benchmark datasets, model aptitude for load characterization and the scalability of the overall system:

- Conventional supervised learning models are predominantly used for natural language processing tasks of NILM that require labelled datasets. In recent developments, to accommodate instances of novel data and heterogeneous operational profiles of appliances, unsupervised learning, semi-supervised learning and hybrid approaches have been researched in depth with the objective of augmenting the efficacy of models.
- Algorithm Categorization: Although the learning paradigm is the main categorization criterion, NILM algorithms are further analyzed in terms of that of the training window size and the target variable type, thus enabling performance improvement.
- Dynamic Load Patterns: Consumer load usage patterns are dynamic by nature and can be prone to temporal variation which can lead to data redundancy. Consequently, the reliability and trustworthiness of machine learning models take a critical position in the empirical evaluation.
- Dependability in AI Models: In order to overcome the above-mentioned issues, there has been a new line of research that questions various scenarios that affect the decision-making ability of AI models in the NILM context.
- The dependability of emerging AI algorithms for NILM is based on the following six key aspects: reliability, scalability, robustness, explainability, fairness, and privacy.

RESULTS AND DISCUSSION

Smart meter hardware continuously monitors energy consumption in real time, processes the sensor data obtained, analog-digital conversion, and gets the result of processing on LCD display. Then the meter sends the aggregated data to a centralized database on an hourly basis. The hardware components have been designed as per the web services, thus enabling remote control of household appliances through a mobile application in the on and off modes. Device actuation is accomplished via a collection of a set of values in a JSON array sent from an internet-enabled Arduino platform. Furthermore, Cloud Messaging of the Firebase has been integrated within a Raspberry Pi in order to send notifications for various events. The smart relays are the middlemen between the Arduino and the home devices and thus remote power control is possible (see Figure 10).

The basic hardware in question includes:

- ESP32 - Works as the control unit which aggregates the data received from the client modules.
- Arduino - Works as reading module, it collects the measurements from the sensors and sends them to the control unit.
- Current sensor - Non-invasive device to

quantify electrical consumption of the devices and relay the data to Arduino.

- Additional components - Encompass resistors, wires, relays, capacitors and similar electronic components.

I²C module - The module allows communicating between the Arduino and the LCD using the least number of pins.

In order to interface with the current sensor, a stereo jack is used to get both positive and negative signals; this signal path is stabilized by a network of resistors (33 o, two 10 k O) and a 10 uF capacitor which in conjunction stabilize the voltage supplied to Arduino, hence within the 5 V limit specified for the device. The overall architecture includes an Arduino Uno R3, LCD display, Ethernet shield with internet connection capability and router for network communication (see Figure 11).

In order to prove such feasibility in practice, a prototype model house was made out of wood and installed with LEDs, an equivalent of household loads. These LEDs are remotely controllable through a mobile application, therefore demonstrating the scalability of the system to real life appliances. In terms of research that focuses on energy disaggregation, the publicly accessible REDD (Residential Energy Disaggregation Data Set) is a rich source of granular data on power consumption from many different households.

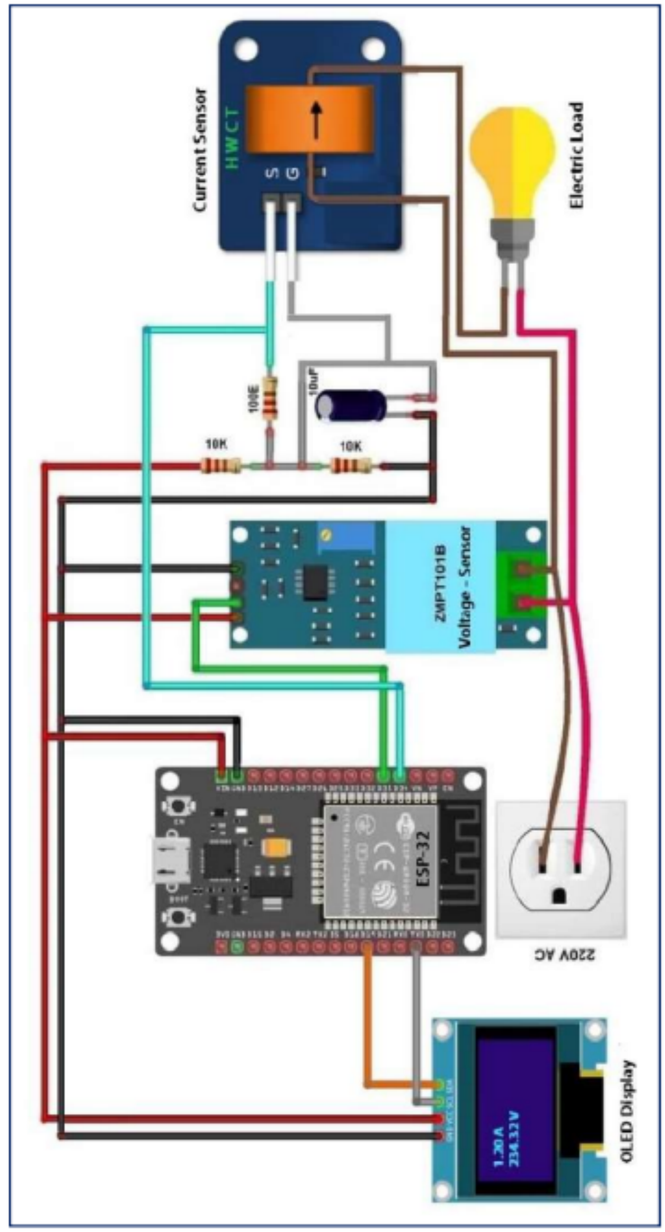

Figure 4: Connection Diagram of project

While machine-learning and data-mining techniques offer encouragement for improving energy efficiency, progress has been limited by the lack of available big data-sets that can be accessed by the public. Consequently, the REDD repository represents an interesting resource for preliminary investigations and low-barrier research in the area of Non-Intrusive Load Monitoring (NILM) research.

4.1.Design Requirements

A burden resistor is very critical to the safe operation of a current transformer (CT). If a CT is connected to a current carrying conductor without a burden resistor it can produce a dangerously high voltage at its terminals which may cause damage to the insulation and destroy the device.

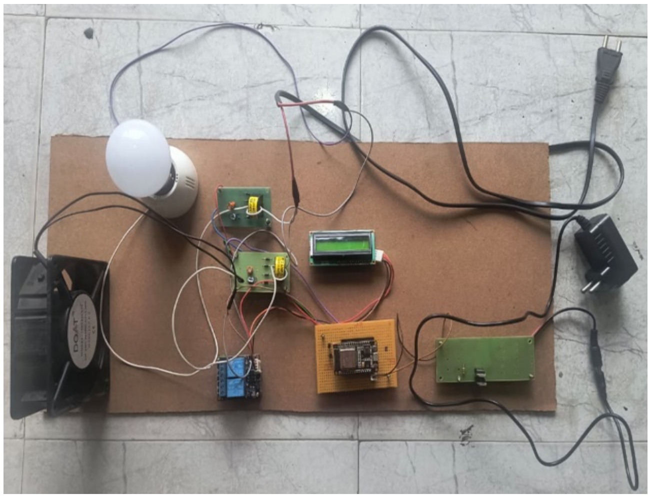

Figure 5: Hardware Model of our Project

Safety Standards for the use of current transformer:

- It is imperative that the current transformer leads should be connected before clamping it around a live conductor, and, likewise, that the transformer should be disconnected from the conductor before removing the leads
- During installation on a live conductor, it is better to short circuit the secondary rather than leave it open.
- Current transformer should not be connected to bare conductor unless it is specifically designed for the purpose.
- Adherence to these precautions is the guarantee for safe operation of current transformer and reduce the risk of equipment damage or personal injury.
- The value of the burden resistor is obtained from the specifications of HWCT, which has a maximum primary current of 30 A.

The calculation will go as follows:

1. Determine the primary peak current:

$$\mathrm{I}_{\text{primary, peak}} = \mathrm{I}_{\text{RMS}} \times \sqrt{2} = 30 \times 1.414 \approx 42.43 \text{ A}$$

2. Calculate the secondary peak current Primary peak current divided by the number of turns in the current transformer (check the datasheet):

$$I_{secondary,peak} = \frac{\mathrm{I}_{\text{primary, peak}}}{Number\ of\ turns} = \frac{42.43}{1800} \approx 0.02357A$$

3. One should choose the burden resistor to get the best resolution: The voltage on the burden resistor at its maximum current should be half of the ADC reference voltage approximately. If the reference is 5 V:

$$V_{burden} = \frac{5}{2} = 2.5V$$

Using Ohm's law, the value of the burden resistor can be calculated as:

$$R_{burden} = \frac{V_{burden}}{I_{secondary,peak}} = \frac{2.5}{02357} \approx 106\Omega$$

Table 1: Home appliances and Current Measurement

Device	I_{RMS} (A)
Vacuum Cleaner	5.80
Fan	0.25
Boiler	3.90
Blender	1.75

The optimum burden resistance for a current transformer is given by:

$$\mathrm{R}_{\text{burden (ideal)}} = \frac{\frac{V_{REF}}{2}}{I_{secondary,peak}}$$

Substituting the given values:

$$\text{Rburden} = \frac{2.5 \text{ V}}{0.023570226 \text{ A}} \approx 106.67\Omega$$

The optimum burden resistance for a current transformer is given by:

$$\mathrm{R}_{\text{burden (chosen)}} = 100\Omega$$

This is to make sure that the peak of the current of the load will not cause a voltage that is greater than 5 V over the burden resistor

Table 2: Metrics values of home appliances energy calculation

Appliance	Precision	Recall	F1-Score	Accuracy
Air Conditioner	0.80	0.85	0.82	0.97
Blender	0.88	0.98	0.93	0.98
Coffee Maker	0.99	0.99	0.99	0.99
Compact Fluorescent Lamp	0.97	0.92	0.94	0.98
Fan	0.84	0.70	0.76	0.97
Fridge	0.90	0.80	0.85	0.97
Hair Iron	0.98	0.99	0.99	0.97
Hair Dryer	0.95	0.92	0.93	0.99
Heater	0.94	0.95	0.95	0.98
Incandescent Light Bulb	0.75	0.87	0.81	0.97
Laptop	0.70	0.91	0.79	0.96
Microwave	0.95	0.88	0.91	0.98
Soldering Iron	0.72	0.98	0.83	0.97
Vacuum	0.99	0.93	0.96	0.98
Washing Machine	0.96	0.89	0.92	0.98
Water Kettle	0.99	0.99	0.99	0.99

Table 3: Average Overall energy consumption monitoring

Day	Energy Consumption (kWh)	Average Temperature (°C)
Day 1	12.8	24.8
Day 2	11.5	24.6
Day 7	10.1	24.7

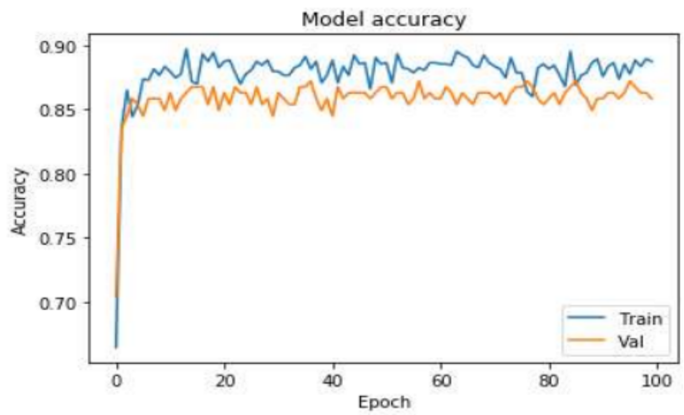

Figure 5: Reliability of Project Energy Estimations

CONCLUSION

The grid application of ICT technology has facilitated a bi-directional communication between the utility and the prosumers, which has led to the introduction of sophisticated methods in power systems. In order to match the energy supply with the demand, demand-response (DR) programs are being implemented. One of the brightest technologies to use in smart grids implementation is the Internet of Things (IoT). Using smart plugs and Fog computing together with artificial intelligence will enable the implementation of DR programs by connecting IoT-enabled smart meters and smart plugs. This paper provides hardware and software solutions to DR programs using the paradigm of the fog-computing. The smart plug is used to measure the frequency of alternating current, RMS voltage and current, power factor and active, reactive and apparent power. These measurements make it possible to identify autonomously the appliance at the smart meter by the machine learning algorithms. A number of lightweight classification processes that could be used in miniature devices were assessed and it was found that the decision tree algorithm delivers the most accurate and the least latent results. The existing Home Energy Management System (HEMS) can work well in case the training dataset includes all the common appliances in the house. Nevertheless, HVAC systems are not regulated by the energy management algorithm to save energy yet ensure that users remain comfortable. Also, there are vulnerabilities since intruders would be able to affect dynamic pricing using smart meters, which would negate the usefulness of the HEMS.

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