Design of Smart Plug for Home Energy Management System

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Abstract: ***With enduring implementation of smart meters, the usage of energy at each level of system can be keep tracked easily. For efficient home energy management, the device level monitoring and control is needed. Energy Disaggregation helps to identify the individual appliance power consumption through a single main measurement of voltage and current. /it also facilitates the process of load monitoring in residential application with minimum intrusion of privacy, hence also termed as Non-Intrusive Load Monitoring (NILM). On increasing significance in areas of Ambient Assisted Living (AAL) and Home Energy Management Systems (HEMS), NILM has extensive application in recent era. This work presents a model for smart plug in which energy disaggregation module is incorporated. The NILM model is constructed using REFIT benchmark dataset and the performance of the model is evaluated.***

Keywords: **Home Energy Management System (HEMS), Smart Plug, Non-Intrusive Load Monitoring (NILM)**

1. INTRODUCTION

W ith the current rate of energy demand, the available natural resources cannot be utilized on long-run. The residential sector in the European Union, alone are contributes for 30% of energy consumption. It is predicted that that global energy demand will get doubled by 2030 and also causes adverse effects on the environment. Literature suggests that buildings' energy consumption can be reduced up to 15% using efficient energy management system. Being the most common and important entity of everyday usage, growing rate of energy demand has grasped the great interest in the area of energy efficiency measures. Consumers can be motivated to adopt the energy conservation pattern in their household energy usage. Demand Response (DR) participation paves way for domestic energy management and also overcome the problems of frequency deviation, which on a closer look needed a self-learning energy consumption feedback. A significant reduction in energy wastage can be achieved through fine-grained monitoring of energy consumption.

With the advent of emerging automation technologies, the smart grid incorporates innovative energy management system to satisfy the growing energy needs of consumers. Recent researches have shown that an efficient tracking of energy usage helps to improve energy efficiency, thereby reducing electricity consumption in residential applications. It can be implemented through Home Energy Management System (HEMS), for which energy usage has to be measured for every appliance. Appliance level energy monitoring can be performed using both intrusive and non-intrusive techniques. However, the Non-Intrusive Load Monitoring (NILM) technique is widely preferred, as it facilitates energy monitoring with less metering infrastructure with reduced sub-metering installation cost. NILM serves as a key to enable efficient demand side energy usage through successive predictions and feedbacks.

2. Home Energy Management System

The Home Energy Management (HEM) market is rapidly expanding alongside substantial investments to improve energy efficiency and upgrade electricity infrastructure to a smart grid. These changes enable consumers to take greater control of their energy use, which can be enabled through the use of Home Energy Management Systems (HEMS).

2.1 Introduction to HEMS

HEMS can be broadly defined as those systems (including both hardware and software linked together via a network) that enable households to manage their energy consumption. This can be done in one (or both) of two ways:

1. HEMS can provide energy consumers with information about how they use energy in the home and/or prompts to modify consumption
2. HEMS can provide the household (or third parties) the ability to control energy consuming processes in the home, either remotely via a smart phone or web service or based on a set of rules, which can be scheduled or optimized based on user behavior.

As such, HEMS enable the delivery of a wide range of both household and utility objectives around energy management, financial benefits, comfort and convenience, greenhouse gas emissions reductions, as well as to ensure access to a reliable energy supply.

2.2 HEMS - Technology Drivers

The HEMS sector is growing rapidly, and there are 12 distinct product types or categories that make up a home energy management system which were identified. These falls into three groups: (1) user interfaces, (2) smart hardware, and (3) software platforms, as shown in Fig.1.

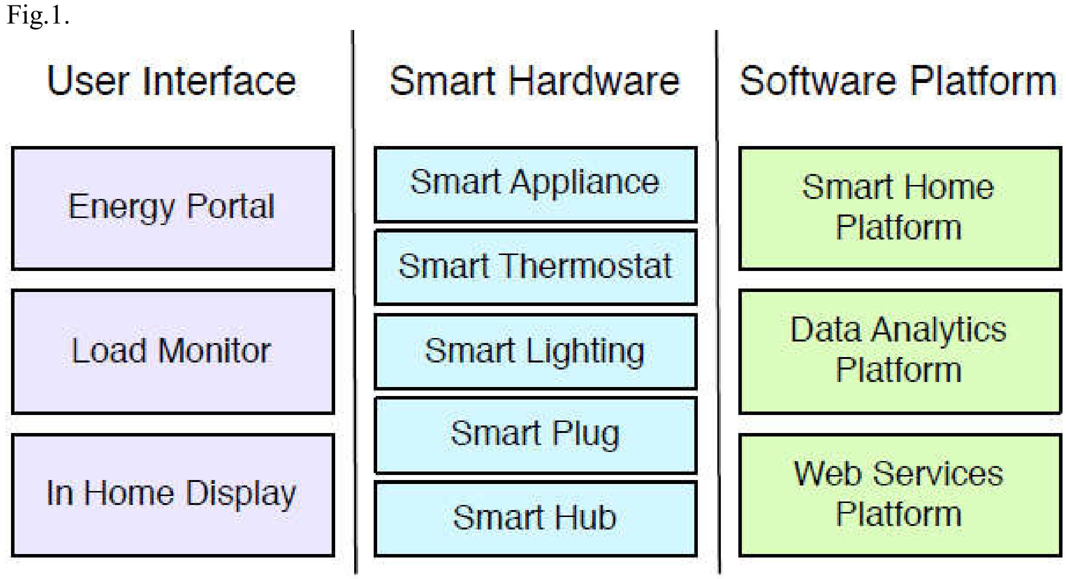


Fig.1 – HEMS- Technology Drivers

User interfaces include: energy portals, in-home displays, and load monitors, whose primary function is to incorporate the user into the home energy management process by providing them with information to help make more informed energy use decisions and/or enabling them to implement remote or rule-based control. Smart hardware, including appliances, thermostats, lighting, plugs, and hubs, describes those products that physically enable household energy demand to be controlled such that the energy demand patterns of particular appliances are modified to meet particular objectives.

Software platforms facilitate the communication of information between users, utilities, and hardware in the home. They include: (1) smart home platforms, which deliver a managed environment and provide core services to enable a standardized way for devices and appliances to interact; (2) data analytics platforms, which are typically hosted on the cloud and analyze large volumes of data to provide additional insights about energy use patterns; and (3) web services platforms, which provide end-users additional functionality for managing connected devices.

The rapid expansion of the HEM market and the desire for increasing levels of interoperability between products and platforms has led to the emergence of new types of communication protocols and alliances based on these. Over the coming years, this may open up the opportunity for further engagement between manufacturer and a variety of developers to create fully integrated home management solutions that better meet the needs of customers.

2.3 Smart Plug

A smart plug is defined as a separate piece of hardware that serves as a proxy between the energy source and energy-consuming device, which can control and/or provide feedback about the energy-consuming device (Fig.2). Smart plugs include outlets, switches, power strips that enable users to control devices and appliances plugged into them. They enable control signals to be sent to connected appliances via remote commands or algorithms that are built into the device or reside in the product cloud. Many smart plugs can additionally provide feedback about the energy consumption of connected appliances. Most smart plugs enable users to remotely control the devices plugged into them via a smart phone and accompanying mobile app or other via any Internet-enabled device.

Fig.2 – Smart Plug

2.4 Layout of Home Energy Management System

Energy consumption in the residential sector represents an important part of the total electricity demand. In this context, a proper prediction of energy demand in housing sector is very important. Energy use in home accounts for significant part of total energy consumption both in developing and western world. Residential buildings currently account for large part of the total energy demand. This system is an important part of the smart grid and has many benefits such as:

- ✓ Reduction of the electricity bill
- ✓ Reduction of demand in peak hours
- ✓ Meeting the demand side requirements

One of the HEMS objectives is to decrease the peak demand of households by controlling power intensive loads and in the same time take into account the comfort and priority of the customer. Home energy management system allows the households to regulate power of the smart devices after receiving a signal from the service provider. “There are two energy consumption peaks during the day: in the morning, between 8 and 10 AM, and in the night, between 6 and 10 PM. The role of cost control is to change the load curve shape in such a way that energy consumption peak decreases, even though the total consumption for the specific household is the same”.

Energy prediction for appliances in homes has a great influence in the functioning of a home energy management system. This system is able to determine the best energy assignment plan and a good compromise between energy production and energy consumption. The Home Energy Management System is mainly composed of Smart plugs, Gateway, Web server, Database and a user devise.

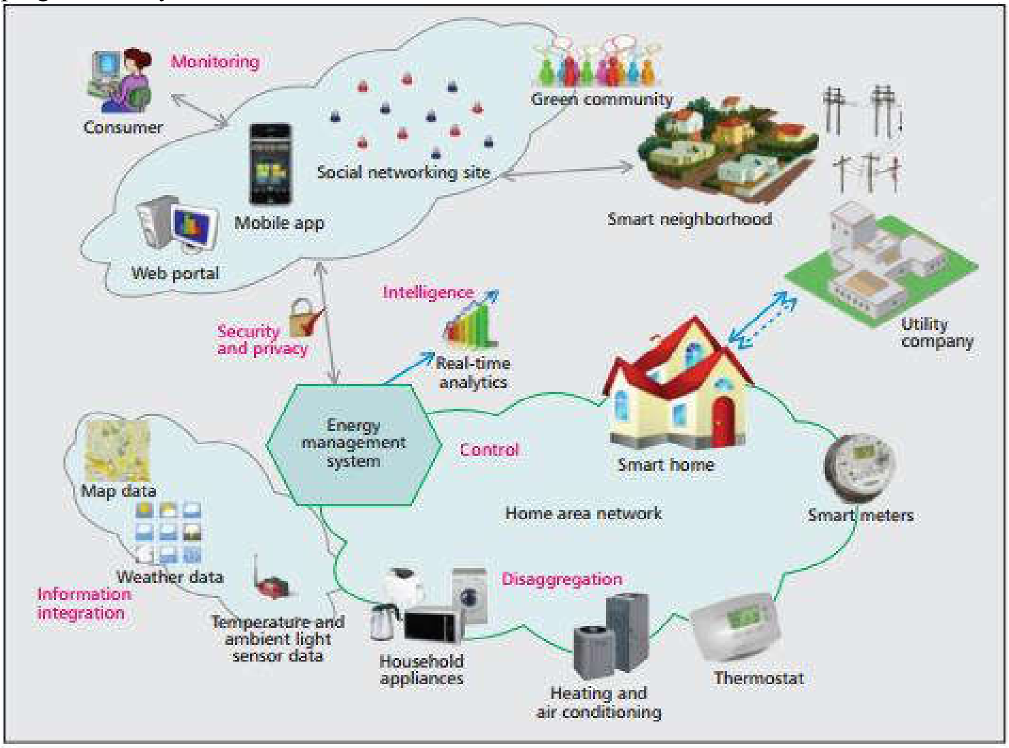


Fig.3 – Layout of Home Energy Management System

Fig.3 explains the key parts of the Home Energy Management System and the main requirements for HEMS that will help the monitoring and control of energy. The requirements are stated as follows:

- ✓ **Monitoring:** provide the frequent energy consumption information by the system to the consumer.
- ✓ **Disaggregation:** the system has to provide disaggregated data about each appliance. From the information given by the system, the impact of specific appliances and the impact of long term changes can be clearly highlighted.
- ✓ **Availability and accessibility**: Information should be provided at all times with an easy to use interface.
- ✓ **Information integration**: in addition to providing disaggregated data. The system should provide other kinds of information that are related to different appliances like: temperature , humidity, etc …
- ✓ **Affordability:** The system should be easy to install and have minimal consumption.
- ✓ **Control**: The consumer should be able to control manually its devices.
- ✓ **Cyber-Security and privacy:** The system must ensure that consumer's data are secure and private.
- ✓ **Intelligence and Analytics:** The system has to be able to take some intelligent decisions taking into consideration the data available.

2.5 Need for Non-Intrusive Load Monitoring (NILM) in HEMS

While Advanced Metering Infrastructure generates operational efficiency for utilities, the societal benefits are far from reality; especially in the residential sector, where behavioural barriers exist that impede the realization of significant energy savings. Consumers, today, have Motivators such as neighbourhood comparisons, competitions and social platforms, but lack the Engagement Tools to help them make informed energy saving decisions. The tools that exist are either relatively expensive or target one-time appliance-related efficiency gains only. Traditional energy dashboards present consumers with historical consumption and generalized energy saving tips, but lack specific actionable recommendations. Consequently, the energy savings delivered by these dashboards are limited to 1-2% of household consumption.

Energy Disaggregation (or) Non-Intrusive Load Monitoring (NILM) refers to a set of statistical approaches for extracting end-use and/or appliance-level data from an aggregate, or whole building, energy signal without any plug-level sensors. It is one of the most anticipated energy data analytics technologies in the residential and small commercial sector. It enumerates a consumer's energy bill, analyzes energy use and cost for each of their household appliances, and makes truly personalized and prioritized savings recommendations – all this without any plug-level sensors or in-person audits, at a massive scale, and at a lower expense level than ever possible before.

3. Test Case and Hardware Setup

The proposed work of our project is to find the loads which are connected to the plug. The Smart plug which contains Energy Disaggregation Model, if needed can use internet and android application for transferring data.

3.1 Design of NILM Model

The Energy Disaggregation Model or NILM model contains Data Acquisition and Pre-Processing, Learning Algorithm which finds the Load State with the help of Appliance Database as shown in Fig.4.

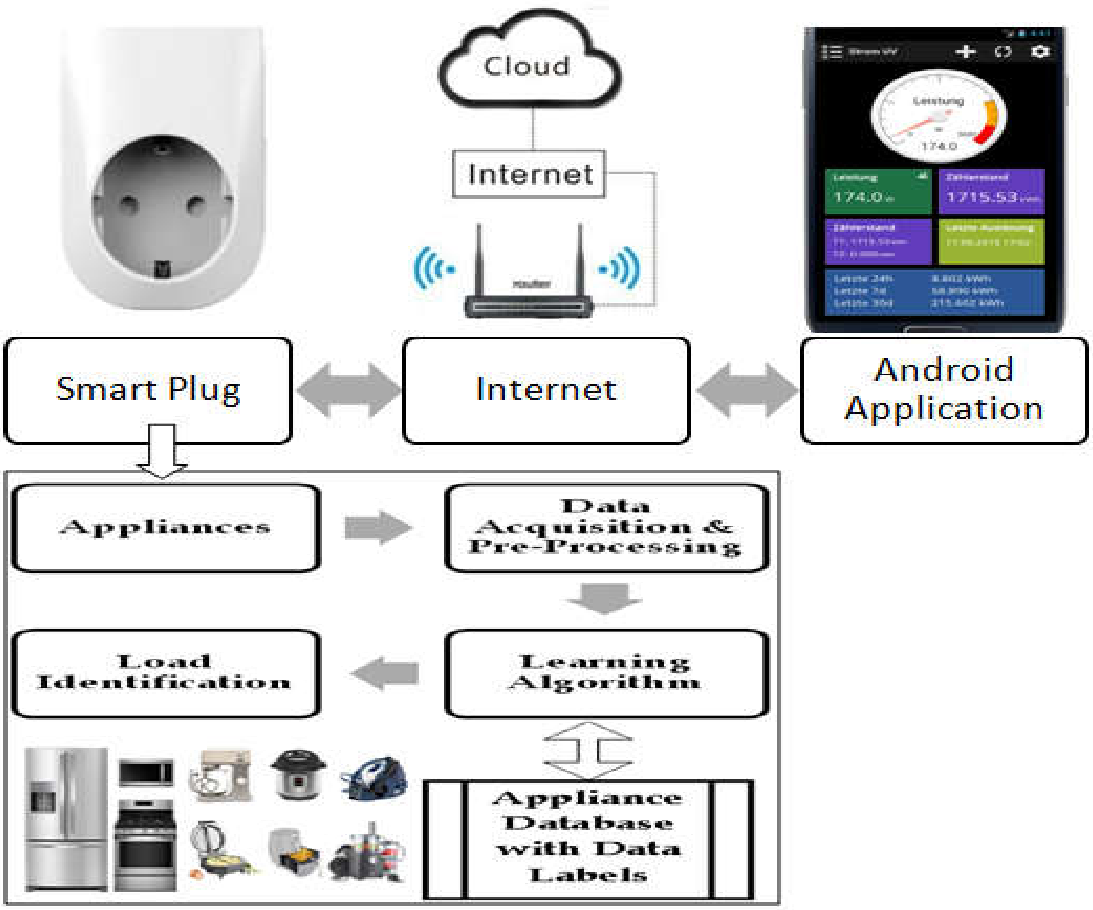


Fig.4- Proposed Design

The basic five steps involved in the standard load characterization are as follows:

- ***Sensing and Data Collection:*** Electrical parameters are measured at sensing node with predefined sampling rate.
- ***Data Pre-processing:*** Collected information is pre-processed using suitable technique to eliminate the data redundancy.

- ***Feature Extraction and Classification:*** From pre-processed data, the essential features are extracted for characterizing the load efficiently.
- ***Event Detection:*** Using available load signature data, the model predicts the event (OFF/ON/ON-multi-state) occurrence with unseen data samples.
- ***Model Evaluation and Validation:*** The trained model is tested with unseen samples and the various performance metrics such as accuracy, precision, recall and the rate of true positive and false positive are evaluated.

3.1.1 Learning Algorithm

The learning algorithm used here is **classifier learner** .Classification is a two-step process, learning step and prediction step, in machine learning. In the learning step, the model is developed based on given training data. In the prediction step, the model is used to predict the response for given data. Decision Tree is one of the easiest and popular classification algorithms to understand and interpret.

Decision Tree Algorithm Decision Tree algorithm belongs to the family of supervised learning algorithms. Unlike other supervised learning algorithms, the decision tree algorithm can be used for solving regression and classification problems too.

The goal of using a Decision Tree is to create a training model that can use to predict the class or value of the target variable by learning simple decision rules inferred from prior data (training data).

3.2 Reference Dataset

There were many datasets available for the studies related to NILM as referred from Literature. Fig. 5 show the most commonly used datasets for energy disaggregation in NILM model. These datasets are available for open access in website and can be accessed on a request basis. A detailed description of each of the dataset shown in Fig. 2 follows herein.

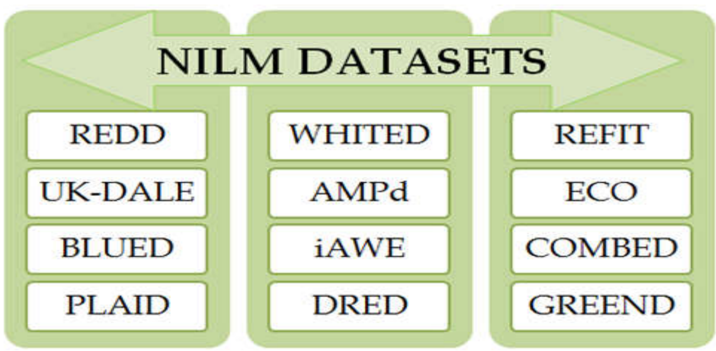


Fig.5 - Disaggregation Datasets

In this work, the REFIT reference dataset is used. This dataset was collected in 20 UK homes in the Loughborough area over the period 2013 – 2014. The process of data collection is a part of project titled Personalised Retrofit Decision Support Tools for UK Homes using Smart Home Technology (REFIT), supported by the Engineering and Physical Sciences Research Council (EPSRC) which is collaboration among the Universities of Strathclyde, Loughborough and East Anglia. For every 8 seconds, the active power signal was measured from 9 individual appliance channel monitor along with aggregate signal. The list of appliances used in various houses of this dataset is depicted in table 4.1.

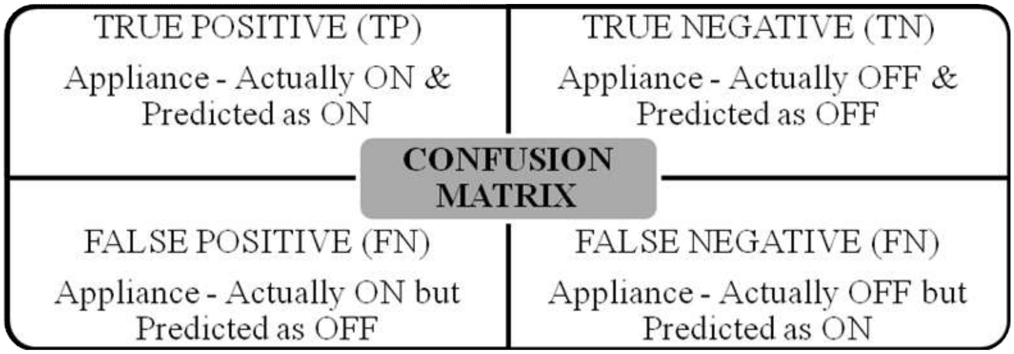
Table 1 – REFIT Dataset – List of Appliances

House No.	**List of Appliances (Channel 1- Channel 9)**
1	Fridge, Freezer_1, Freezer_2, Washer_Dryer, Washing Machine, Dishwasher, Computer, TV, Electric Heater
2	Fridge-Freezer, Washing Machine, Dishwasher, TV, Microwave, Toaster, Hi-Fi, Kettle, Overhead Fan
3	Toaster, Fridge-Freezer, Freezer, Tumble Dryer, Dishwasher, Washing

House No.	List of Appliances (Channel 1- Channel 9)
	Machine, TV, Microwave, Kettle
4	Fridge, Freezer, Fridge-Freezer, Washing Machine(1), Washing Machine(2), Desktop Computer, TV, Microwave, Kettle
5	Fridge-Freezer, Tumble Dryer, Washing Machine, Dishwasher, Desktop Computer, TV, Microwave, Kettle, Toaster
6	Freezer, Washing Machine, Dishwasher, Computer, TV/Satellite, Microwave, Kettle, Toaster, Computer
7	Fridge, Freezer(1), Freezer(2), Tumble Dryer, Washing Machine, Dishwasher, TV, Toaster, Kettle
8	Fridge, Freezer, Washer Dryer, Washing Machine, Toaster, Computer, TV, Microwave, Kettle
9	Fridge-Freezer, Washer Dryer, Washing Machine, Dishwasher, TV, Microwave, Kettle, Hi-Fi, Electric Heater
10	Blender, Toaster, Freezer, Fridge-Freezer, Washing Machine, Dishwasher, TV, Microwave, Mixer
11	Fridge, Fridge-Freezer, Washing Machine, Dishwasher, Computer, Microwave, Kettle, Router, Hi-Fi
12	Fridge-Freezer, Unknown, Unknown, Computer, Microwave, Kettle, Toaster, TV, Unknown
13	TV, Freezer, Washing Machine, Dishwasher, Unknown, Network Microwave(1), Microwave(2), Kettle
15	Fridge-Freezer, Tumble Dryer, Washing Machine, Dishwasher, Computer, TV, Microwave, Hi-Fi, Toaster
16	Fridge-Freezer(1), Fridge-Freezer(2), Electric Heater(1), Electric Heater(2), Washing Machine, Dishwasher, Computer Site, TV, Dehumidifier
17	Freezer, Fridge-Freezer, Tumble Dryer, Washing Machine, Computer, TV, Microwave, Kettle, TV (Bedroom)
18	Fridge(garage), Freezer(garage), Fridge-Freezer, Washer Dryer(garage), washing Machine, Dishwasher, Desktop Computer, TV, Microwave
19	Fridge Freezer, Washing Machine, TV, Microwave, Kettle, Toaster, Bread-maker, Games Console, Hi-Fi
20	Fridge, Freezer, Tumble Dryer, Washing Machine, Dishwasher, Computer, TV, Microwave, Kettle
21	Fridge-Freezer, Tumble Dryer, Washing Machine, Dishwasher, Food Mixer, Television, Unknown, Vivarium, Pond Pump

3.3 Performance Metrics for NILM Model

With widespread applications, the disaggregation model is evaluated using the performance metrics such as confusion matrix indices, recall rate, precision rate, accuracy and F1_score. The confusion matrix for power disaggregation is determined using the values of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). The confusion matrix for learning algorithms is estimated by ON/OFF state of appliances for which energy monitoring is required. Accuracy is the ability to correctly predict the device operation when the device is actually in ON state while Precision is the rate of prediction at which the device is actually in OFF state. Accuracy metrics for the disaggregated dataset will be evaluated for effective implementation. Minimum Classification Error (MCE) criterion is a well-known criterion used in pattern classification for reducing the classification error while handling a new data set.



- $$\text{TP Rate} = \frac{TP}{TP+FN}$$
- $$\text{FP Rate} = \frac{FP}{FP+TN}$$
- $$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$
- $$\text{Precision} = \frac{TP}{TP+FP}$$
- $$\text{Recall} = \frac{TP}{TP+FN}$$

3.4 Hardware Setup

With the societal problem in mind, the hardware designed has to be mainstreamed and relatable to the consumer as much as possible. The hardware section consists of the separate nodes containing a current sensor and a voltage sensor, with the goal of measuring the power consumed for each outlet. Each node consisted of an Arduino to run the necessary sketch, and are all powered by a USB hub. The process blocks involved in hardware layout is shown in Fig.6.

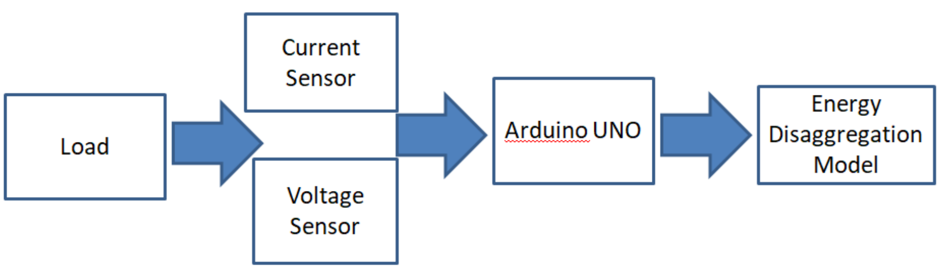


Fig.6 – Hardware Layout

4. Results and Discussion

The hardware setup is designed in such a way to measure the voltage and current of the residential loads using the arduino interface. Also the measured values are transferred to software NILM model as a power value in which the classifier model for each appliance is designed using learning algorithms. The designed hardware for energy measurement is shown in Fig.7.

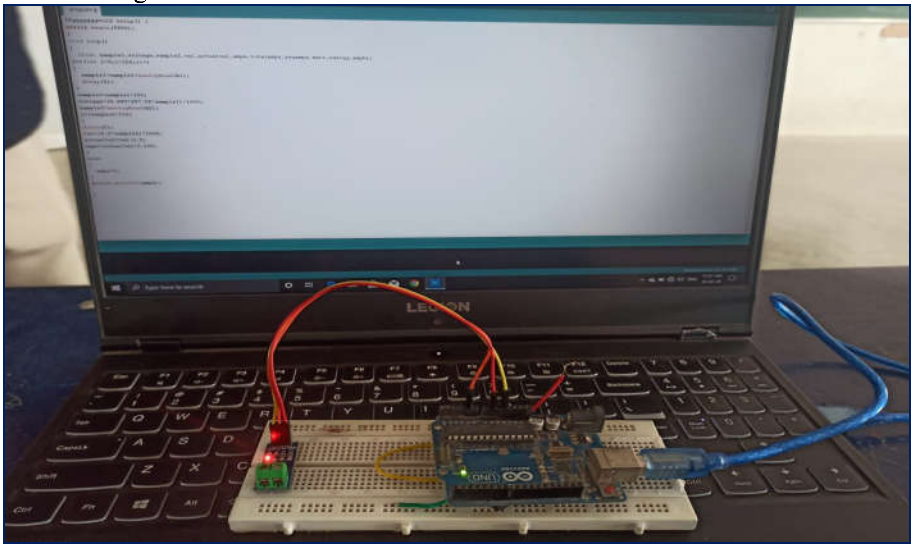


Fig. 7 – Hardware Setup

4.1 Balanced Data Handling Approach

The data handling and pre-processing plays a vital role in enabling the performance of the classifier model. It is always appropriate to use a suitable data handling approach to avoid redundancies in the model performance. Hence, in this design, to ensure better performance model the ON state samples taken at every level of training and testing finds its significance. The ON state samples involved in the process impacts the model to provide appropriate results with better sampling and 80% of such instances are carried over at every process in model building. The details of number of data instances taken for house 1 of REFIT dataset is tabulated below.

Table 2 – REFIT Dataset – House 1 – Data Instances

Appliances	TOTAL	On	Off	Tr_On	Tr_Off	Te_On	Te_Off
Washing Machine	20720	14609	6111	11688	4889	2921	1222
Computer	19441	13387	6054	10710	4844	2677	1210
Dishwasher	13052	6974	6078	5580	4863	1394	1215
Freezer1	32210	26431	5779	21145	4624	5286	1155
Freezer2	37095	31999	5096	25600	4077	6399	1019
Fridge	38273	32711	5562	26169	4450	6542	1112
Heater	34635	34406	229	27525	184	6881	45
TV	23087	17156	5931	13725	4745	3431	1186
Washer	8108	1903	6205	1523	4964	380	1241

The table list the number of sample taken for training (Tr_On & Tr_Off) and testing (Te_On & Te_Off) the model using the total ON/OFF sample instances.

4.2 Performance measures of NILM Model

As discussed in section 3.3, the various performance metrics of NILM model such as confusion matrix indices, recall rate, precision rate, accuracy and F1_score. The confusion matrix for power disaggregation is determined using the values of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). The confusion matrix for learning algorithms is estimated by ON/OFF state of appliances for which energy monitoring is required. The model is build for the prominent nine appliances of House -1 from REFIT dataset. The minimum classification error (MCE) plot, confusion matrix, rate of true positive and false negative was depicted in Fig.8-11. All the above metrics were evaluated for the computer appliance during the training phase of model building using the Decision Tree (DT) classifier.

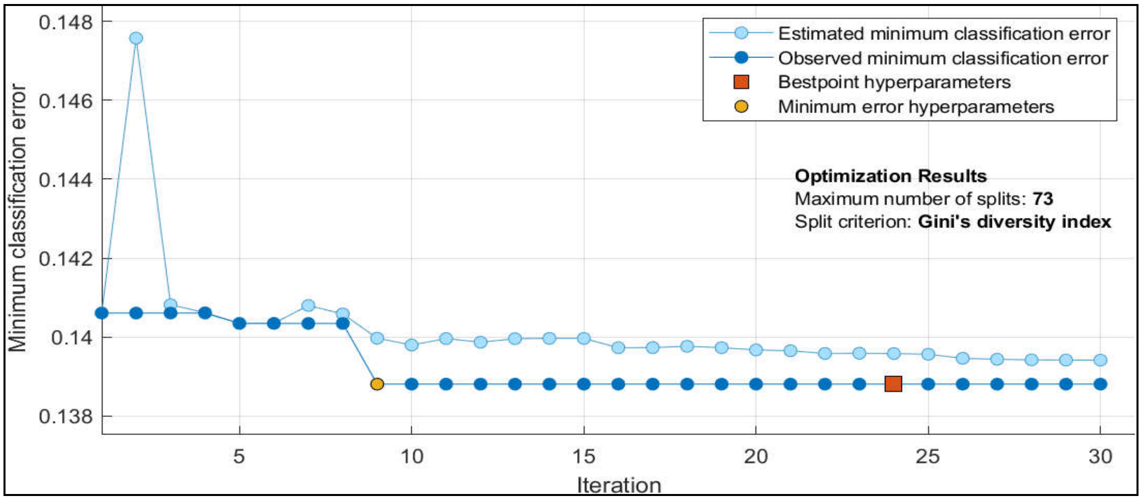


Fig.8 - Minimum classification error plot

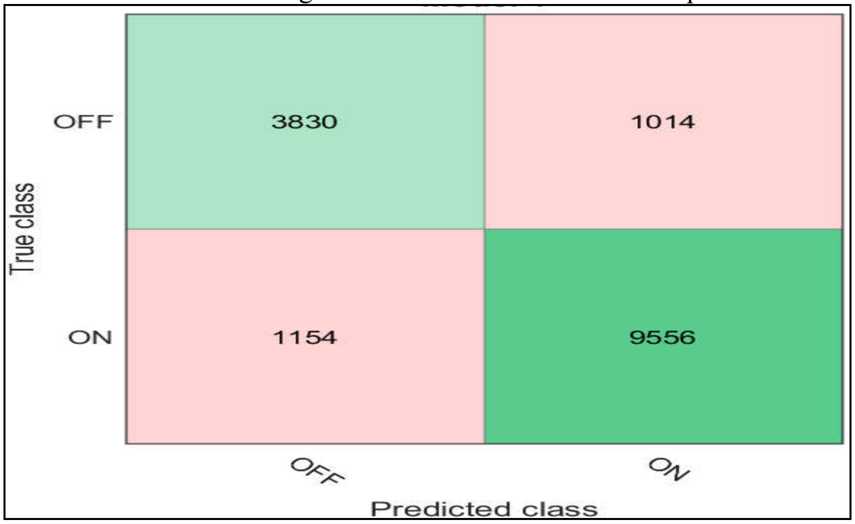


Fig.9 - Confusion Matrix

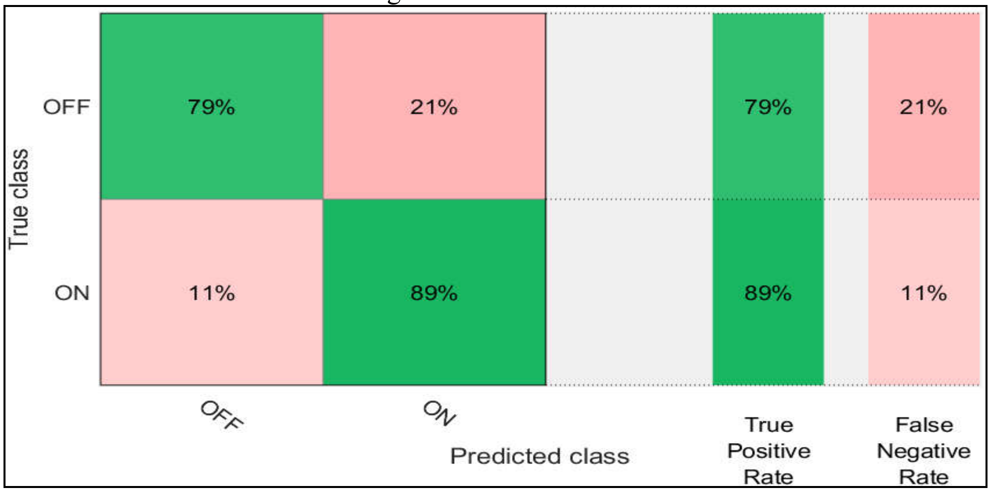


Fig.10 – Rate of Positive Prediction

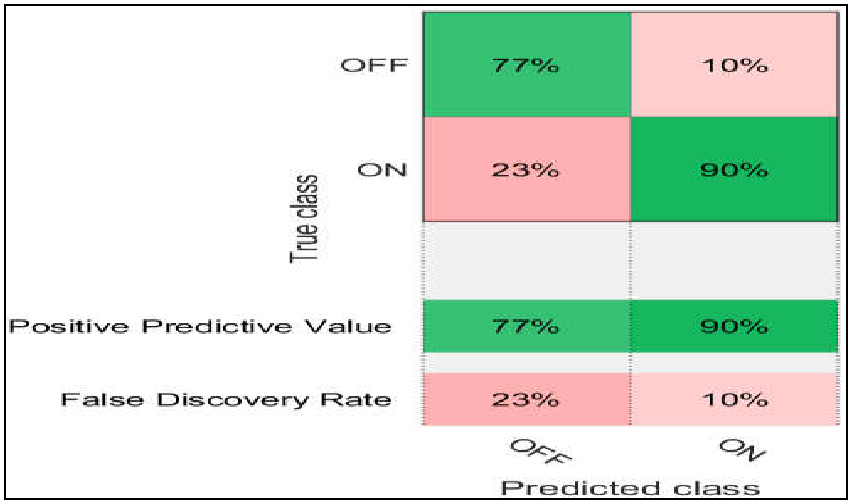


Fig.11 – Rate of True Positive and False Negative

For all the nine appliances, all metrics were evaluated using the different learning classifier and with better results the DT classifier is chosen for model. The results calculated in the training and testing phase of model is enlisted in Table 3 and Table 4.

Table 3 – Performance Metrics for NILM Model during Training Phase

Appliances	TP	TN	FP	FN	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Computer	9556	3830	1014	1154	86.06	90.41	89.23	89.81
Washing Machine	11081	3360	1529	607	87.11	87.87	94.81	91.21
Dishwasher	4487	4090	773	1093	82.13	85.30	80.41	82.79
Freezer1	19875	2441	2183	1270	86.60	90.10	93.99	92.01
Freezer2	25280	353	3724	320	86.37	87.16	98.75	92.59
Fridge	25260	1623	2827	909	87.80	89.93	96.53	93.11
Heater	27525	0	184	0	99.34	99.34	100.00	99.67
TV	12703	2847	1898	1022	84.19	87.00	92.55	89.69
Washer	768	4797	167	755	85.79	82.14	50.43	62.49

Table 4 – Performance Metrics for NILM Model during Testing Phase

Appliances	TP	TN	FP	FN	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Computer	2548	182	1028	129	70.23	71.25	95.18	81.50
Washing Machine	2527	124	1098	394	63.99	69.71	86.51	77.21
Dishwasher	1394	0	1215	0	53.43	53.43	100.00	69.65
Freezer1	5285	17	1138	1	82.32	82.28	99.98	90.27
Freezer2	6384	0	1019	15	86.06	86.24	99.77	92.51
Fridge	6507	12	1100	35	85.17	85.54	99.47	91.98
Heater	6880	0	45	0	99.35	99.35	100.00	99.67
TV	3337	67	1119	94	73.73	74.89	97.26	84.62
Washer	165	635	606	215	49.35	21.40	43.42	28.67

5. Conclusion

The main motivation behind this work of smart plug for home energy management system is to save energy through real time feedback system. The reference REFIT energy disaggregation dataset helps to develop a load identification model for wide range of appliances involved in 20 different houses. NILM model developed is validated using different types of learning classifier algorithm such as decision tree, naïve bayes classifier, k-nearest neighbour and support vector machine. Out of which, decision tree NILM model provides the better result in terms of classification accuracy and precision. The real time feedback system incorporated with NILM model helps to identify the operation of load in residential application. This type of smart plug inbuilt in home energy management system reduces the number of sensing units thereby reducing the cost and the complexity of the design. The designed smart plug with energy disaggregation module support the better load identification and further it finds the many extensions. Smart plug for main metering can be employed for overall system monitoring with efficient control over appliances. The proposed design for residential application can further be extended to commercial and industrial application for any specific system design.

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12. *The author Sandeep Pirbhulal Heye Zhang Md Eshrat E Alahi Hemant Ghayvat in this paper" A Novel Secure IoT-Based Smart Home Automation System Using a Wireless Sensor Network ".*