ELECTRICITY AUDIT INCORPORATING NON-INTRUSIVE LOAD MONITORING

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Abstract: **Electricity monitoring has become increasingly important as the concept of energy management and conservation has gained popularity, whether it be industrial, commercial or residential consumer or the utilities providing electricity. Despite being such an essential tool it is still practiced in an outdated style. The whole process is tedious, time consuming, completely manual with a trade-off on accuracy. The purpose of this paper is to provide an automated solution with a high level of accuracy, swiftness and proficiency using a technique called Non-Intrusive load monitoring. NILM provides an advantage of acquiring the complete data of a building at a single measuring point and then disaggregating the complete waveform into respective devices using artificial intelligence. To implement NILM, data acquisition module based on Arduino due was developed and then the disaggregation is done on MATLAB using K-means toolbox. The paper present one mode of disaggregating the waveform using steady state analysis of devices and the results were displayed on MATLAB.**

Keywords—non-intrusive load monitoring; energy management; signature space; classification algorithm; k-means clustering; Arduino data acquisition; MATLAB Simulation.

I. INTRODUCTION

As the world is facing the problem of energy crisis, the demand of energy management and conservation is on its peak. Electricity audit has therefore become a primary task for many of the bigger projects. It helps its user to determine the energy consumption, maximum demand, and power factor measurement and to check the efficiency of the electrical appliances in use. It proves to be vital to overcome energy losses. Not only this as we move towards the smart grid we cannot ignore the importance of energy audits. The audits are carried out either in a traditional method of installing sensors at every other device and then collecting the data from different sensors through wireless transmission. The other way is to manually collect the device ratings, monitor their turn on duration, record their current ratings with the help of clamp-on ammeter and then to do all the calculation manually. In each of the above-mentioned method there is chance of error. If any one of the sensors malfunction the whole data will be corrupted and will not remain valid. Similarly taking the readings manually also requires full concentration if any of the device rating is incorrect then the whole process of calculation should be repeated.

The concept of Non-intrusive appliance load monitoring was introduced by George W. Hart in 1992. The technique was designed to monitor an electrical system that comprises of individual appliances turning on and off independently. The major advantage of NILM is that there is only a single point of data measurement and so the need of installing sensors at every other appliance is effectively eliminated. For this reason, it is termed **non-intrusive** as the appliance data gathering is autonomous of intrusion onto energy consumer's property.

The traditional method of load monitoring comprises of a complex hardware design but with a relatively simpler software version. The usage of NILM reverses this statement by having a simpler hardware and a complex and efficient software to separate the loads from an aggregated load waveform. This is however the most cost-effective advantage of NILM in many of the applications. Nevertheless, there are certain disadvantages of NILM as well which are evident in other applications.

The following section of this paper discusses the NILM framework and its terminologies, the hardware design implemented, the algorithm for disaggregation and the results.

II. NILM CONCEPT & TERMINOLOGIES

The concept of NILM can be summarized in form of a single equation:

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$$P_i(t) = \sum_{k=1}^{n} P_k(t)$$

Where P_i is the total power consumed and is equal to the aggregate of 'n' individual device power P_k. the task of NILM is to decompose this power into its constituent devices. [2] Through various sophisticated analysis of total load NILM estimates the nature and number of individual loads along with their consumptions. Since only a single sensing point is available so NILM provides a convenient and effective method in contrast to the traditional method. Recently this method is gaining popularity due to the advancement in embedded systems. [1] In general, NILM could be defined by two of its major components; appliance signature and classification algorithm.

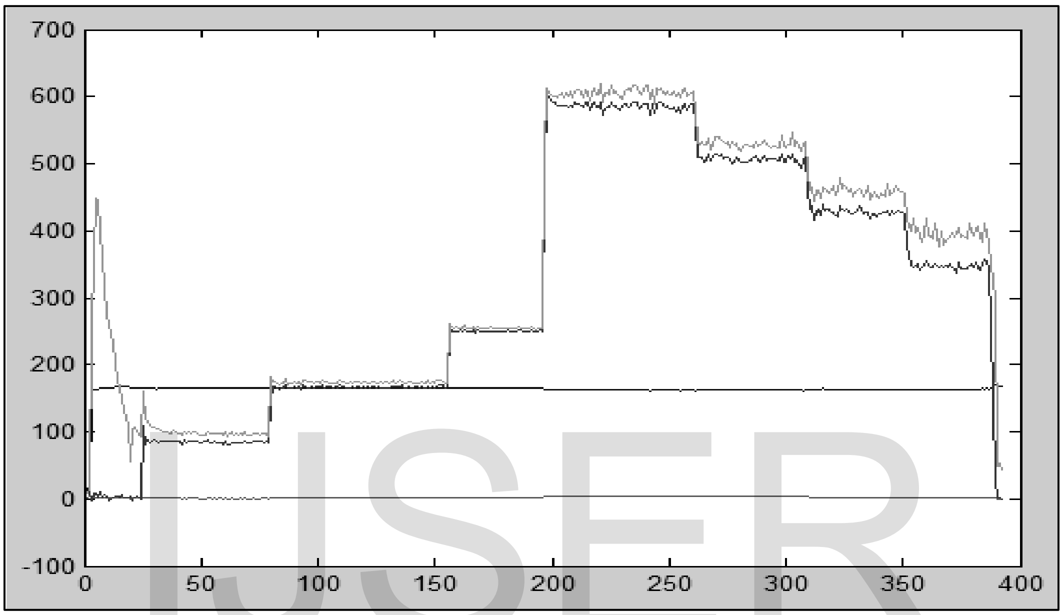

Figure 1: Aggregated Voltage, Current, Real and Apparent Power versus Time (obtained from true data acquisition model)

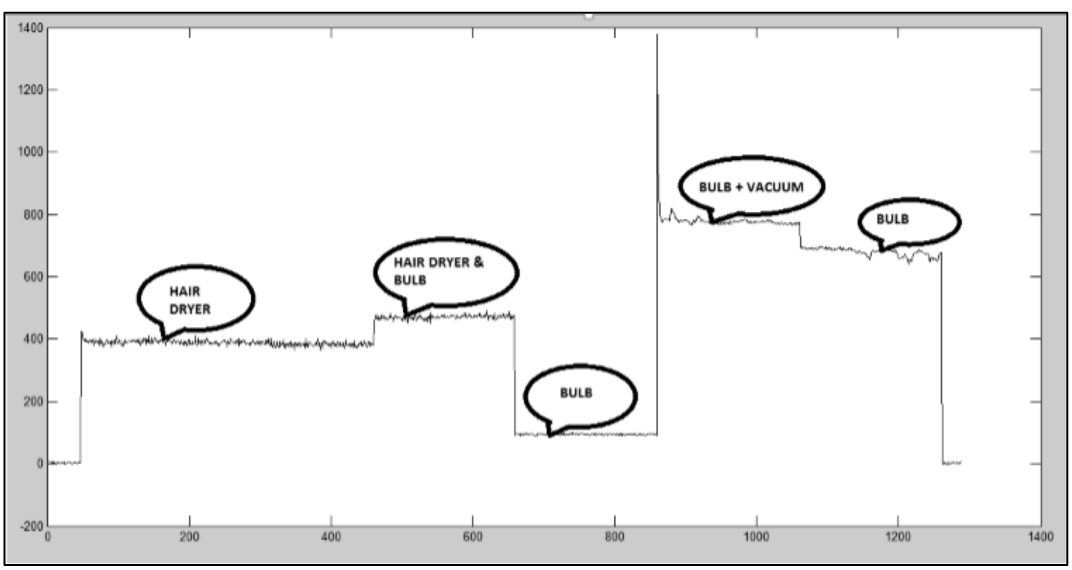

Figure 2: Power Vs Time (obtained from original data acquisition model)

A. NILM General framework:

The implementation of Nonintrusive load monitoring begins with the data acquisition stage. The energy consumption pattern of the building or area under observation is collected by means of voltage and current sensors. The features of interest are then separated out from the sampled data and then finally the load identification algorithm is applied. The process is summarized in figure 3.

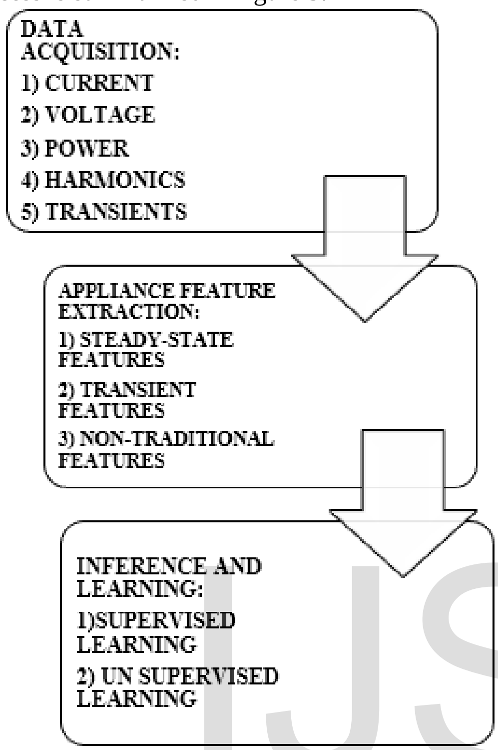

Figure 3: General Approach to NILM

B. Goals of NILM:

There are two major goals of NILM depending upon the level of intrusiveness which are as follows:

Manual Setup has an intrusive setup period in which the signatures of appliances are recorded as on or off but it is entirely different from intrusive monitoring as during the setup mode no hardware can enter the area under observation. During the second stage of normal mode the step changes are matched with the recorded one in database. [3]

Automatic Setup as the name suggest it is more advanced as compared to manual setup. It has no setup stage rather it sets itself up automatically. As the data is coming it separates the major clusters out of it and with which appliance it is linked to. [4]

C. Types of Loads:

The loads are broadly classified into three types and each one of the type is modelled accordingly. The following are the classifications:

Type-I: This type includes the load that have only two working states either ON or OFF. These loads are modelled as a Boolean switch function. This is a good approximation for many of the household appliances like incandescent bulbs, heater, toaster etc.

Type-II: This type includes loads that have more than two operating states e.g. cloth dryer, refrigerator, three-way lamp etc. and thus they are modelled through Finite State Machine (FSM) model. The circle indicates the state and the arrows indicate the possible switching between different states along with the change in power level. These loads are characterized as Multi-state loads. They are easily identifiable because their switching pattern is repeatable. [5]

Type-III: This type includes the loads that are continuously variable devices e.g. fan dimmer, power drills etc. Their power consumption is not a fixed value rather its variable with infinite number of states in between thus it becomes quite challenging for the algorithm to detect such loads.

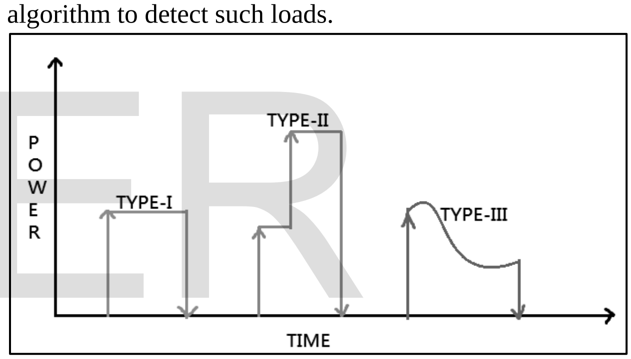

Figure 4: Types of Loads

D. Signatures:

The appliance feature or signature is heart and soul of NILM and hence should be handled carefully. The algorithm is designed based on these signatures. The signature of an appliance distinguishes it from the other appliances. Every device has a unique signature and hence by learning that signature the device can be detected easily from the collective waveform just as the name of the person makes him prominent among many others. The appliance signatures can be intrusive and non-intrusive [6], since our focus is on non-intrusive so only those signatures will be discussed under this heading.

Non-Intrusive Signature occur during normal operation of the device for example the step change in the real power. These signatures are further classified on the basis that whether this change is present throughout the appliance working mode (steady-state signature) or just for a brief time duration (transient signature)

Steady-state Signature: These signatures are based on the steady state operation of an appliance. The most fundamental steady-state signature is that of real (P) and reactive power (Q). If the load is purely resistive then voltage and current are in phase and hence no reactive power. For purely inductive load the situation reverses and thus no real power. However, real power is not just the only steady-state signature we can also make use of admittance. Using real and reactive power may sometimes give erroneous results because the voltage supplied by utilities varies 5% and so does the current and so the resulting power varies 10%. Another problem with power signatures is that devices with same power consumption cannot be identified by the algorithm. Researchers [7-9] have tried using the real power as a disaggregating feature and found out that loads with high power consumption are easily detectable whereas the detection of appliances having overlapping signatures is a challenging task.

The limitation of power signature can be resolved by using harmonics along with the power signatures which improves the overall performance of the detection algorithm. Most of the electronic based devices have harmonics. This makes the signature of different devices less overlapping. But for capturing the harmonics of an appliance higher sampling rate is required.

There are two major advantages of using steady state features firstly, continuously present indication is easier to observe than momentarily occurring identity. Secondly the steady state signatures are additive which means if two events happen simultaneously then their step change will be the sum of both of them.

Despite of incorporating all these signatures and constant advancement the steady state analysis is not that efficient especially for industrial and commercial use. But a great choice for monitoring a residential building. Figure 5 shows the steady state signature space having loads that were used in our project implementation.

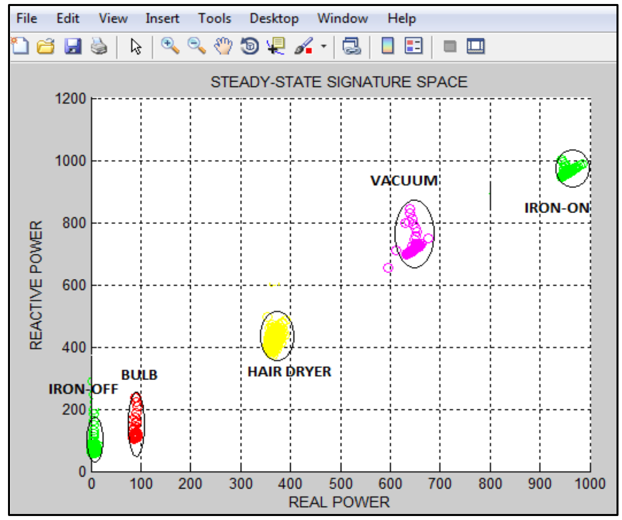

Figure 5: Steady-state Signature Space

Transient Signature: To overcome the disadvantages of steady state signatures a new signature class was tested by the researchers [11] that included the turn-on transient's energy and time period of different electrical appliances for the purpose of load disaggregation. This proved useful when the two loads have similar power consumption. The steady-state signature was additive as well as temperature dependent. The longer a device operates the greater power it consumes. Unlike steady state the transients are not additive or temperature dependent. Because the transient occurs for very short duration of time and in the starting therefore it does not account for operational temperature. When considering transient for load disaggregation then four things must be in focus:

SHAPE: transients in consumer appliances comes in various shapes depending upon the mechanism of generation.

SIZE: transients have different sizes for different appliances depending on how much starting current they draw.

DURATION: the time duration for which the transient appears, it varies from device to device.

TIME CONSTANT: the rate at which the transient decays out is termed as its time constant.

It has been shown that [12] transient response time and their energies are better features than steady-state for load disaggregation. However, repeatability of transients and high sampling rate are its major drawbacks. [10]

Non-traditional Signature: Some appliances unveil certain features that are difficult to characterize as transient or steady state. They are mostly related to

appliances that does not hold much interest for the utilities but are important to analyze the complete appliance behavior. One such signature can be observed in washing machine due to cyclic reversal of the washing tub. Though it is not present through entire wash cycle but during the time when major power is consumed.
Such unusual signature suggests how complex a FSM model might be to capture the complete behavior of an appliance. [13]

E. Disaggregation Methods:

There are two approaches for the NILM disaggregation. One is supervised learning which mostly comprises of optimization and pattern recognition. And the other one is unsupervised learning that consist of clustering. In supervised learning there are two stages of training and testing respectively and hence it requires a dataset to train the system. The training needs some special hardware which increases the human efforts and cost. Thus, the researcher [15-17] are now actively looking for unsupervised method so that the training step is eliminated. Many research papers incorporate these techniques in detail. Figure 6 summarizes this heading. For our project we have selected the supervised learning technique.

III. HARDWARE DESIGN

The hardware design consists of two portions:

- Data Collection Module.
- Data storage Module.

In the collection module the major components are the voltage sensors, current sensors and Arduino due processor. Whereas in storage module the major component comprises of a micro SD card of 2GB and micro SD card jacket.
Figure 7 and 8 [18-20] shows the hardware of the project.

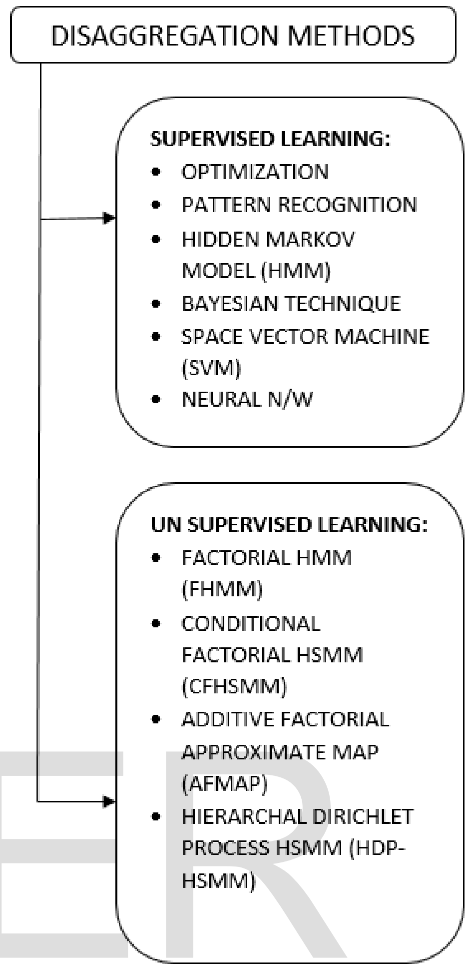

Figure 6: NILM Disaggregation Methods

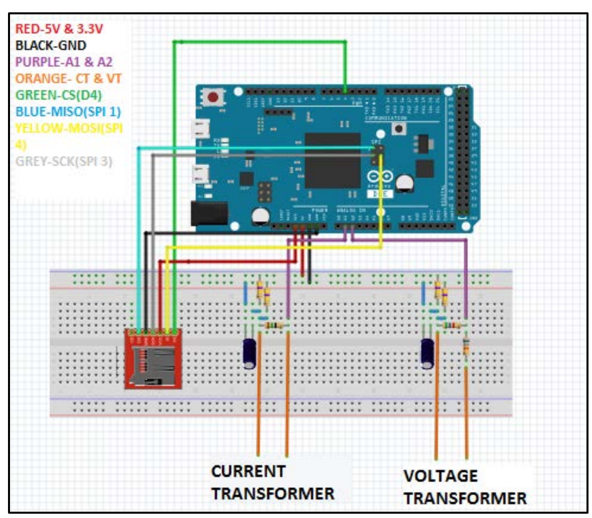

Figure 7 Breadboard View of Hardware (Fritzing)

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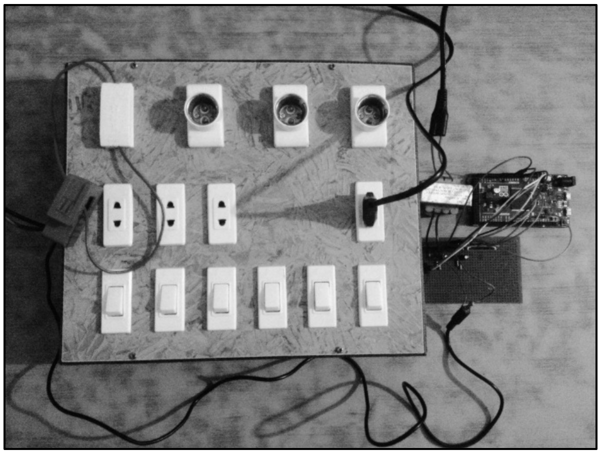

Figure 8: Hardware Design (Collection and Storage)

A. Data Collection Module:

Data acquisition module is one of the most important parts of this project. To apply NILM algorithms a huge set of data is needed, therefore an accurate measurement circuit must be made. Our data collection is done through an Arduino Energy Monitor [21] and uses Emon library which measures main voltage and current. The key components of this energy monitor are CT sensor and voltage transformer, an interfacing circuit which interface CT and VT with Arduino due and SD card interfacing circuit. To understand the working of energy monitor we first must understand the function of these key components.

Current Sensor & Interfacing Circuitry: For current measurement we used current transformer SCT-013-000. It is a split core CT having a single primary winding and thousands of secondary windings. When using a CT its secondary should never be left open-circuited. But some CTs like the one we used in project have in built protection of Zener diodes and sometimes come with built in burden resistor if the CT's output type is voltage.

For the CT to be interfaced properly with the Arduino due; the output of the CT should be conditioned as there are certain input requirements of the Arduino Due. [22] There are two portions of the interfacing circuitry:

- **CT sensor and the burden resistor**: the CT used in the project have current output and does not have a built-in burden resistor therefore to convert current into voltage a burden resistor is required. The calculation of the burden should be done very carefully because if we use a burden greater than the desired value then resultant voltage will be greater than Arduino reference voltage. The burden used in the project was of 15Ω.
- **The biasing voltage divider:** The voltage divider is an important part of interfacing. Originally the signal oscillates around 0 so it has both positive as well as negative values whereas Arduino accepts only the positive values so a DC bias equal to half of the Arduino reference voltage is provided using a voltage divider and the signal then oscillates around that DC value making it positive and acceptable for Arduino Due.

Voltage Sensor & Interfacing Circuitry: For the purpose of voltage measurement, the simple step-down transformer of 9V was used. In the similar manner as that of CT interfacing circuit, the signal conditioning of output of the VT is incorporated in order to meet the input requirements of the analog inputs of Arduino [23]. The interfacing circuitry has two portions just like the CT interfacing:

- **Scaling down the output coming from VT.**
- **Adding a DC offset to eliminate negative component.**

The first part of the interfacing circuitry can be achieved by simply dividing the voltage using voltage divider. While the second part of voltage biasing is being implemented precisely like CT interfacing circuit.

Figures 9 and 10 shows the CT and VT circuits and their corresponding waveforms.

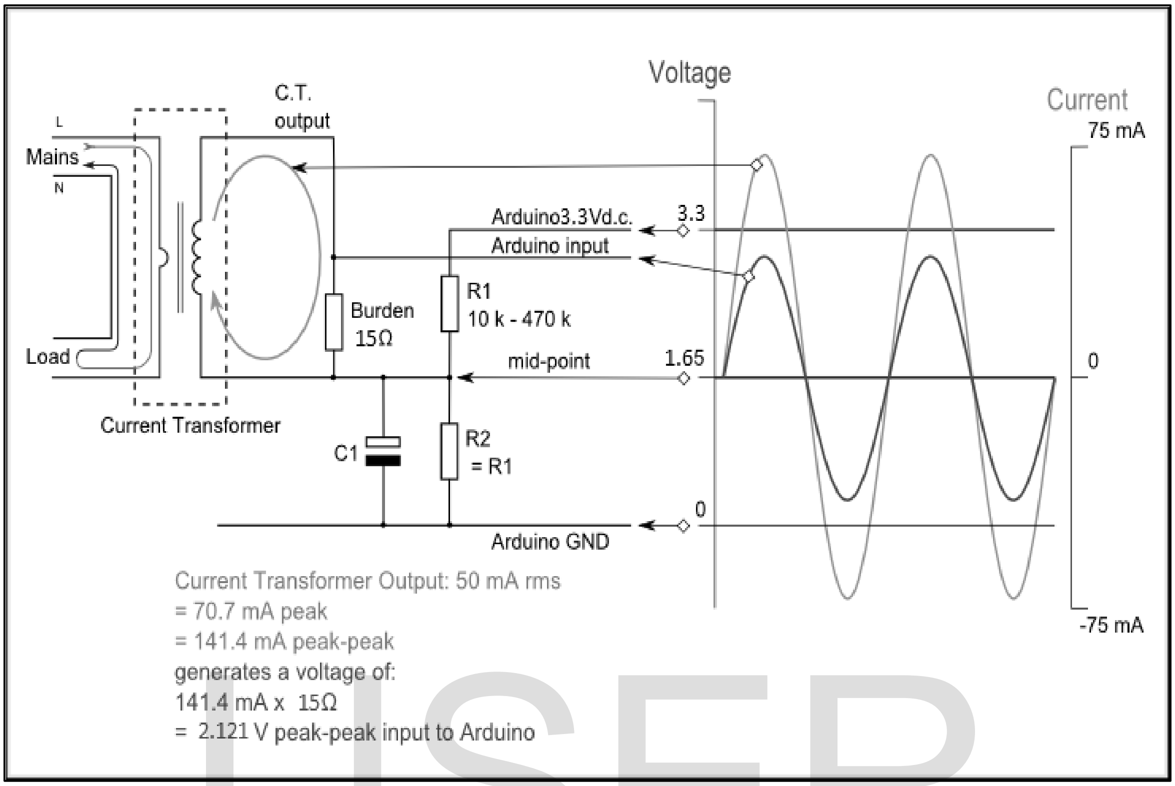

Figure 9: CT Interfacing Circuit and Waveform

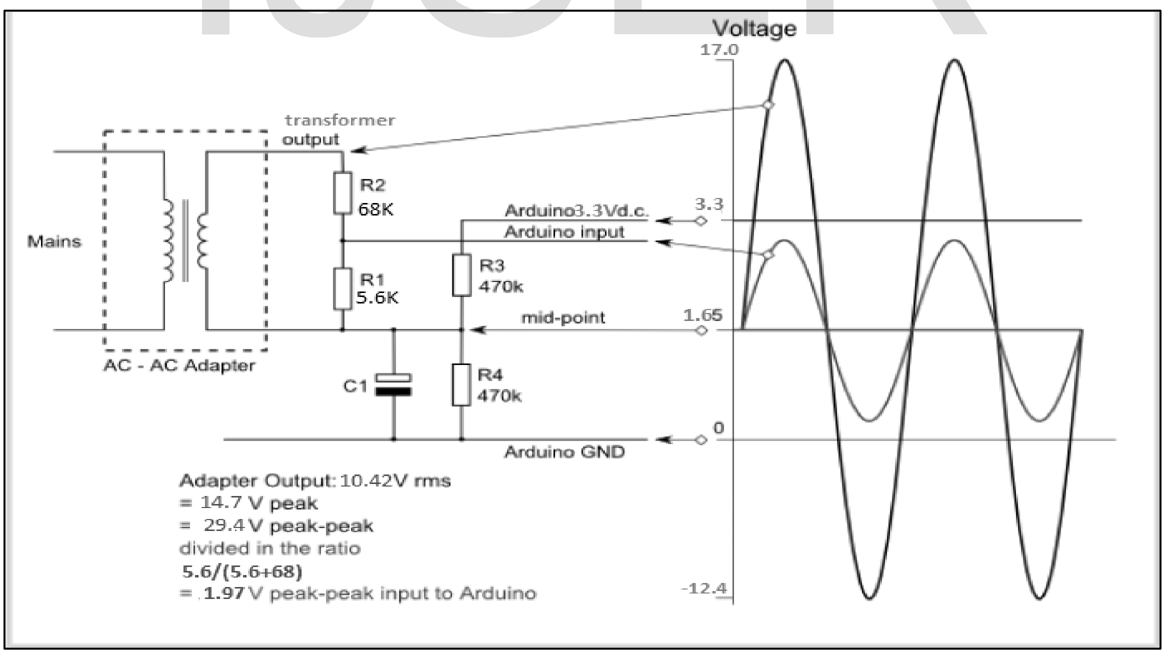

Figure 10: VT Interfacing Circuit and Waveform

B. Data Storage Module:

The data acquired from different loads plays a vital role in the implementation of this project and throughout the project a series of extensive data from numerous loads has been extracted, thus we needed a storage device to handle large amount of data. To interface SD card with Arduino due we need a SD card breakout.

SD card interfacing: There are Arduino shields (like the modern Ethernet shield) that allow you to attach an SD card to your Arduino. However, it is possible to directly attach an SD card to an Arduino [24, 25]. To interface the SD card with Arduino due the following steps must be followed:

1. Format the SD card on FAT32 or FAT16 file system.
2. The following connections should be made between the SD card breakout and Arduino due SPI pins:

- SPI pin 1 (MISO) of due is connected to MISO (DO) of the card reader.
- SPI pin 4 (MOSI) of due is connected to (DI) of the card reader.
- SPI pin 3 (SCK) of due is connected to SCK of the card reader.
- Digital pin 4 (D4) of the due is connected to the CS of card reader.
- GND pin of due is connected to the GND of card reader
- 3.3V of due is connected to the VCC pin of card reader.

3. After making all the connection the code should be uploaded from the example codes of SD card on Arduino due and the details could be checked on the serial monitor.

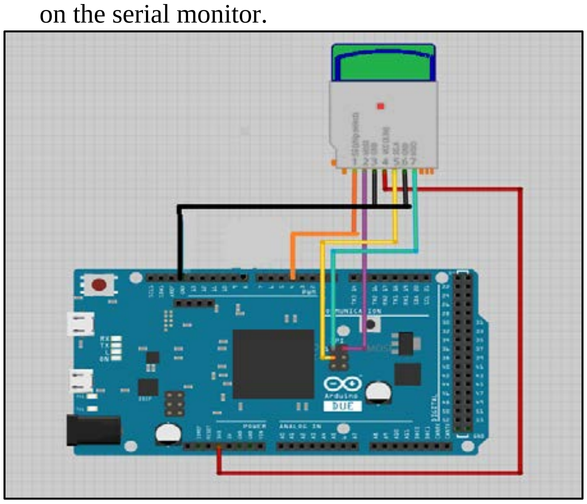

Figure 11: SD card breakout Interface (Fritzing)

C. Hardware Calibration:

To accurately sense and measure the voltage and current from CT and VT, our circuit needed to be calibrated.

The mains voltage and current are being measured by transforming them to a safe lower level and are being further divided before applying to microcontroller's analog input. The analog input measures this voltage relative to 3.3V which is the supply voltage of Arduino due then scales it to a reference voltage which would give $2^{10} = 1024$ maximum count.

Since the current is also measured in terms of voltage, the microcontroller sees these voltages in the form of counts, which is equal to:

$$\boldsymbol{counts = (input\ or\ analog\ pin\ voltage \div 3.3) \times 1024}$$

in order to get the meaningful form of the voltage it is multiplies by a constant known as calibration constant,

$$\boldsymbol{V = count \times voltage\ constant}$$

$$\boldsymbol{I = count \times current\ constant}$$

The error in the readings is not unusual, it can be due to external influences, CT's transfer ratio, the accuracy in measuring the burden voltage etc. however the uncertainty in the readings can be minimized by calibrating the device time to time. Calibration can be done by using two multimeter one for voltage and one for measuring current and resistive load or loads; in our case we have used three bulbs and a hair dryer. We have used power analyzer for observing the mains voltage and current. The readings of the power analyzer and serial monitor were compared for different loads (bulb and hairdryer) and by hit and trial method calibration of each factor was done. Firstly we have adjusted the current calibration constant and then voltage constant.

The calculation for new calibration constant was done by using the following formula:

$$\boldsymbol{New\ constant = existing\ constant \times (correct\ reading \div obtained\ reading\ from\ Arduino)}$$

IV. DISAGGREGATION ALGORITHM:

As previously stated that the implementation of NILM could be achieved by various techniques [26, 27] either through supervised learning or unsupervised learning. The method adopted for disaggregation in our project is K-means clustering technique.

There are two approaches that have been followed for the disaggregation of waveform into its ingredient devices. Both the algorithm designed are based on k-means clustering and are tested on the project prototype and the readings are the real data of the

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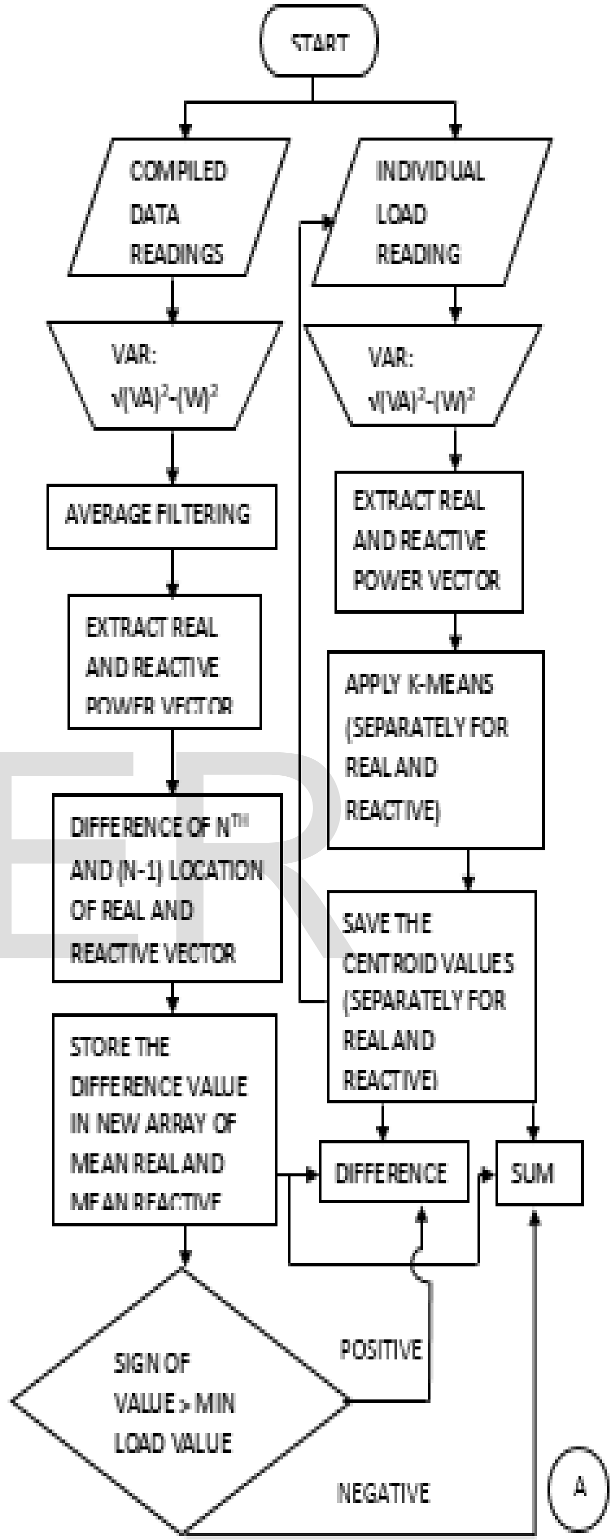
devices collected through our hardware module. The starting of the steps is almost same in both the algorithm but after that different paths have been followed. The following is the flow chart of the code that has been designed using k means.

A. First Algorithm:



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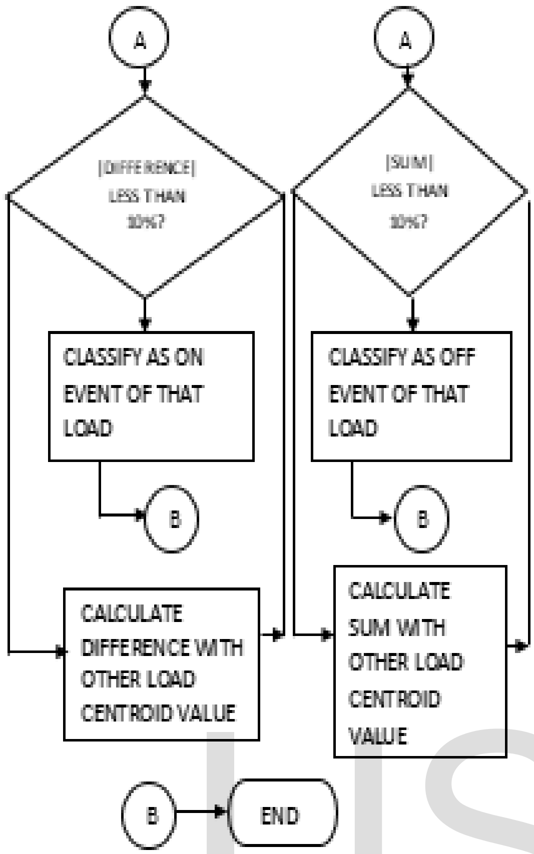
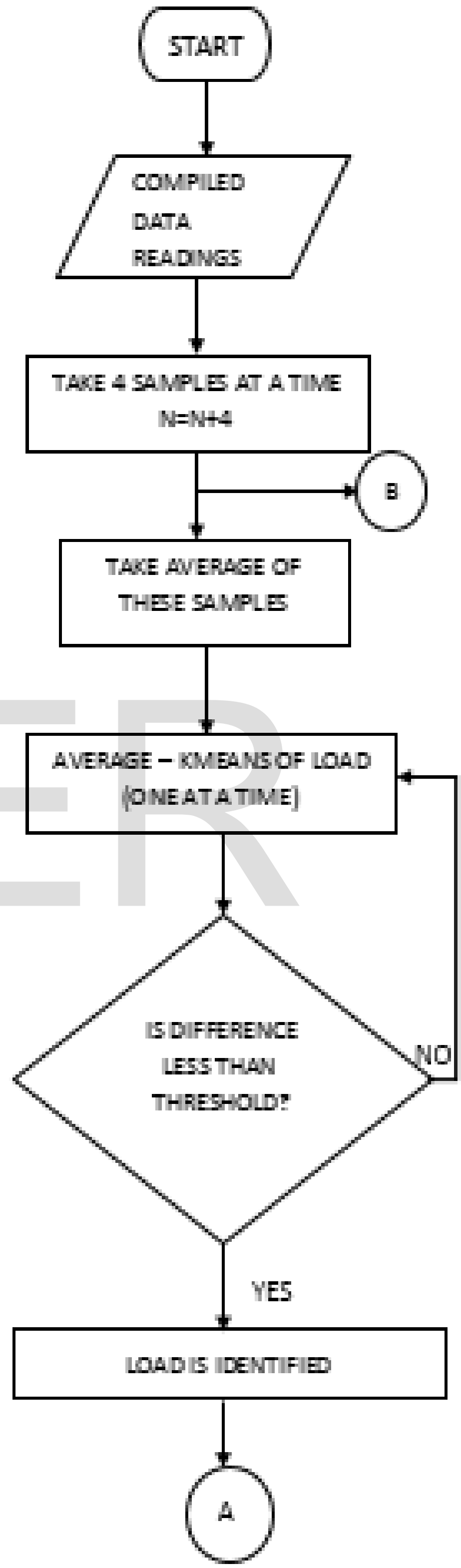
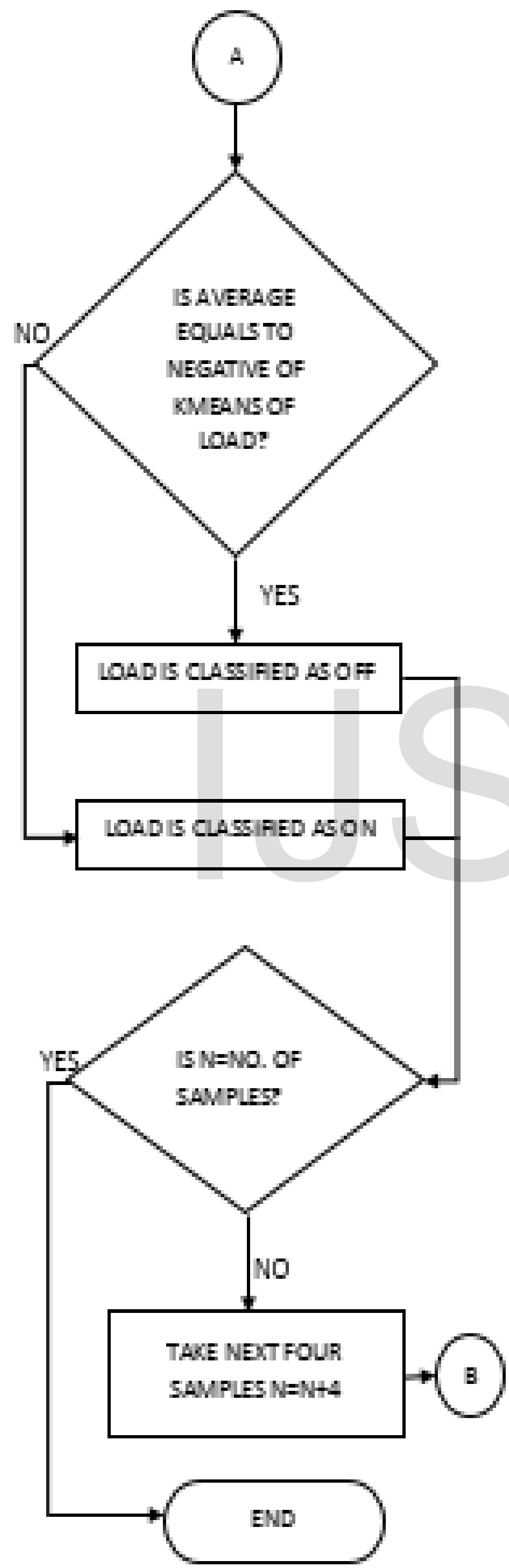


This algorithm has been tested on the loads selected for our project and it works quite satisfactorily. The code runs for all the samples but only those locations are considered for difference or sum whose value is greater than or equal to minimum load value in the mean array. The difference or sum is calculated with each centroid load value one by one. Wherever the difference is minimum it is classified as that load.

B. Second Algorithm:

The following algorithm has also been tested and verified on the loads that were selected. The flowchart of the algorithm is as follows:





V. TESTING AND RESULT:

All the discussion done above have been verified and tested on our designed prototype. Before stating the results of the experiment, it is important to mention out a few things:

A. Load Selection:

The scope of our project is presently restricted to the residential loads of power above and equal to 100W. This limitation is however concluded after observing data set of numerous loads. The loads having power lower than 100W were very difficult to detect incorporating our NILM algorithm hence CFL, LED etc. were excluded. The appliances having similar power profiles were difficult to identify e.g. computer and bulb have similar power ratings. Moreover, permanent consumer appliances e.g. smoke alarm, Wi-Fi routers etc. and continuously variable consumer devices e.g. dimmer were also excluded since our NILM algorithm was only able to detect on-off state devices. Thus, based on the above criteria our selected loads are bulb, iron, hair dryer and vacuum cleaner.

B. Testing Phase:

The testing phase begins with data acquisition from the load box. For data collection we need to install Arduino 1.5.3 and add the Emon library as it is not already present in it. The code designed was uploaded and verified. Care should be taken while setting the baud rate. Once the code is verified the data could be seen on the serial monitor. The code written automatically saves the text file in the SD card.

Initially the individual load readings were taken and plotted for finding their K-means using Matlab toolbox.

The hardware designed had a sampling rate of 25 samples/sec which is quite low but still acceptable for the devices and signature we worked on. Figure 12 shows the real power versus time plots of the devices selected. But for the steady state signature we need plot of real and reactive power and the k-means of every individual device is evident in figure 13. After the k-means of devices are saved as variables in Matlab, the aggregated waveform is then taken by switching on the loads one by one.

The algorithm is then applied on the aggregated load data which point out the step changes in the data known as edge detection. The aggregated waveform is shown in figure 14, the blue waveform is the aggregated load waveform and the overlapping green lines shows the step changes. The positive green lines indicate the switch on state and the negative lines shows the switch off state of a device. The figure shows the zoom in view of the waveform.

The data tips are mentioned on every step change in the waveform and the same results are indicated on command window of the MATLAB as the algorithm runs on the aggregated data and verifies that the results are correct.

Table 1 shows the snapshots of MATLAB command window.

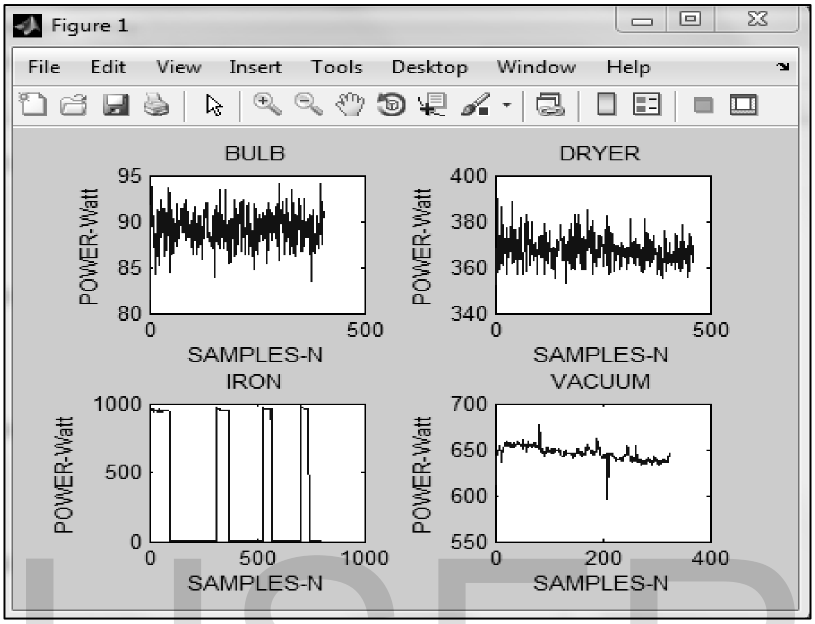


Figure 12: Real Power versus Time Plots

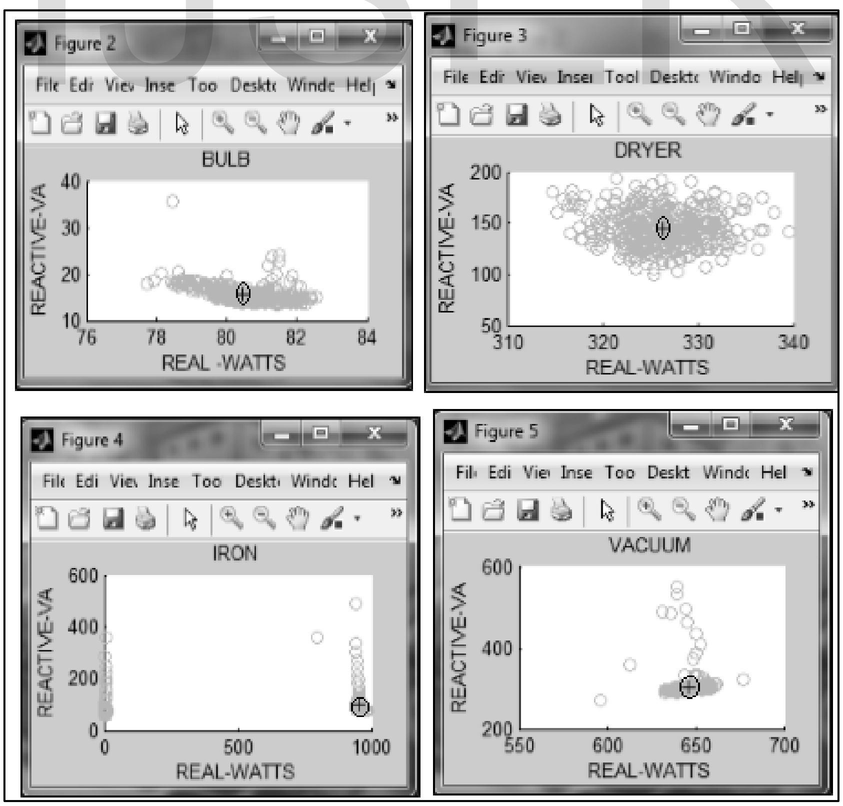


Figure 13: K-means Centroid

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C. Limitation of Project:

The limitations which had potential impact on the work include:

A. Small devices (under 100W) cannot be detected. The power consumption of any device varies at maximum to 100W. Hence smaller loads would overlap with the consumption pattern of larger loads and cannot be recognized.

B. The load signatures have been plotted incorporating two features; active and reactive power. Thus, the devices which are identical in terms of active and reactive power cannot be distinguished.

C. The devices should not be switched on or off simultaneously. Otherwise it would result in overlapping of the power consumption pattern leading to improper identification of loads. Moreover, for appropriate acquisition of data and recognition of devices, the microprocessor requires a time delay of at least 20 seconds between every switch on and switch off.

However, these limitations can be significantly alleviated by incorporating additional analysis features such as harmonic current signatures, transients for recognition of devices.

Further modification is required by the designed algorithm to overcome all these limitations. These limitations are temporary and our project restricted only.

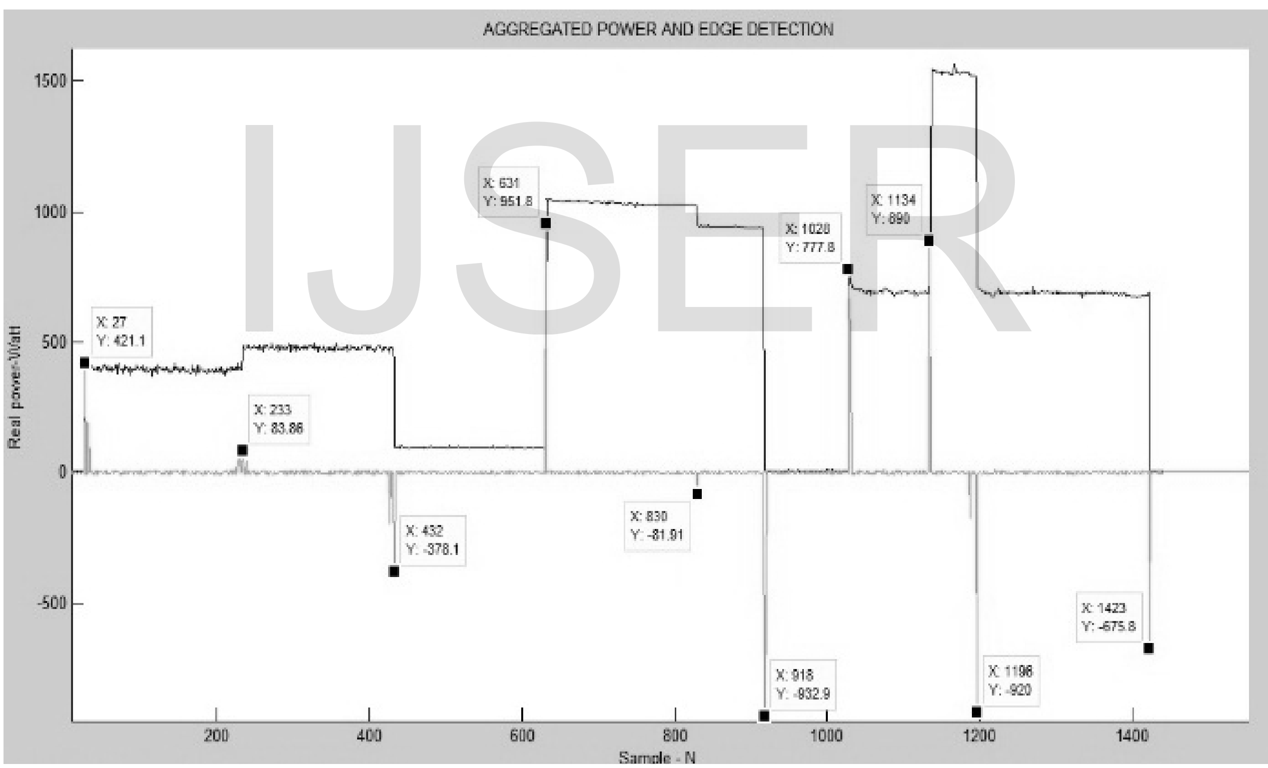
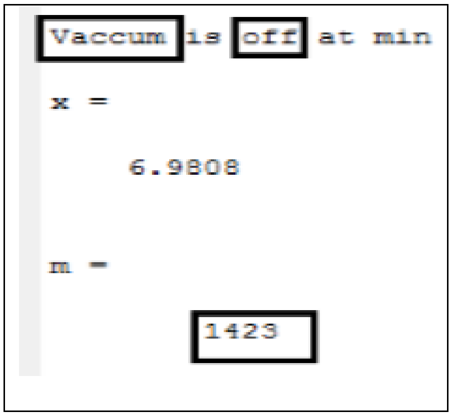


Figure 14: Aggregated and Edge detections

Table 1: MATLAB Results

Command Window DRYER is on at min x = 0.1325 m = 27	Bulb is on at min x = 1.1430 m = 233	Command Window DRYER is off at min x = 2.1192 m = 432
Iron is on at min x = 3.0955 m = 631	Command Window Bulb is off at min x = 4.0717 m = 830	Iron is off at min x = 4.5034 m = 918
Command Window Vaccum is on at min x = 5.0430 m = 1028	Iron is on at min x = 5.5630 m = 1134	Iron is off at min x = 5.8672 m = 1196



VI. CONCLUSION AND FUTURE WORK

Summarizing, the core objective of the project was inclusion of automation in electricity audit systems to provide meaningful higher accuracy and rapid results. The automation tool utilized was NILM (non-intrusive load monitoring). NILM technique enchanted the domain of electricity auditing leading to a more cost effective, reliable and efficient power system network. Since it suffices both the user and the supplier with the knowledge of electricity consumption patterns. This particularly benefits the sector of demand side management.

The project was an integration of hardware and software. The employment of non-intrusive load monitoring initiated with the formulation of prototype comprising of data collection module and interfacing circuitry. The parameters computed includes current, voltage, active power, reactive power and power factor. This was followed by the selection of required features from the sampled data and then the application of NILM on them. NILM is an attractive method for energy disaggregation, as it can discern devices from the aggregated data acquired from a single point of measurement unlike conventional auditing. The data was interfaced from Arduino to MATLAB where all the data was represented in the form of graphs and analyzed.

Thus, our goal was to devise a basic scheme for the benefit of industrial, commercial and residential sector in terms of energy conservation. Automated electricity audit signifies 80% lesser time than conventional auditing, the use of microprocessor make it highly sophisticated, reliable and efficient system. Furthermore, the device was formulated from off the shelf elements so it is cost effective. The project is just a globule in the field of energy audit and with improvised algorithms holds great potential for the future engineers.

A. Future Consideration:

Significant future work includes the development and testing of modified algorithms to explore various load signatures. Optimization can be done for the detection of constantly operating loads like clocks and multistate appliances such as washing machine. Moreover, the information from data collection module can be transferred to the computer via Wi-Fi.

Synchronization can be done with industry standards. The device can be implemented for three phase circuits providing feasibility to industries. This is obtainable by replicating the hardware twice along with few modifications in the coding.

Currently the device is performing post processing. However, the incorporation of real-time software application would benefit in real time processing. The data will directly transfer to MATLAB and will be processed at the same time resulting in better utilization of resources.

NILM holds smart grid compatibility with the same motive of two-way communication between consumer and the utility. The consumer and supplier will be aware of the usage pattern of energy and thereby it would be easier to monitor and improve energy consumption of loads. The benefit would be appropriate use of energy with reduced electricity costs and more efficient and reliable power system.

VII. REFERENCES

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