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Electrical Load Identification for Household Appliances

Ritesh Purrahoo[1], Bhimsen Rajkumarsingh[2]
Department of Electrical and Electronic Engineering, University of Mauritius, Mauritius
[1]riteshpurrahoo@gmail.com
[2]b.rajkumarsingh@uom.ac.mu

***Abstract* — Electrical energy is one of the leading sources of production and of crucial significance in nowadays life. Energy saving is a key element and hence, efficient management of energy in buildings is pivotal to reduce electricity consumption. For this motive, it is essential to provide individual appliance energy consumption data to homeowners with the use of efficient assets and thus, the overall energy consumption obtained from the house main circuits must be disaggregated into separate device. Electrical load identification helps determine the type of load, operating conditions and electricity consumption of electrical appliances. This work examines different identification techniques based on power signature of household electrical appliances obtained from Reference Energy Disaggregation Dataset (REDD) system which uses a single electricity sensor connected to a building's main circuit to measure aggregated energy consumption. Each distinct algorithm extracts dissimilar features for analysis and classification. Various sets of samples were generated for simulation purposes to evaluate the proposed methods. From results obtained, we were able to identify the appliances chosen for use within a certain level of inaccuracy. The Load Switching Transient (LST), Mean Steady State (MSS) and Discrete Fourier Transform (DFT) algorithms have been determined to have overall accuracy of 99.8%, 97.1% and 100% respectively based on the samples generated for simulations. Finally, the DFT method was deemed to be unsuitable for use in practise to its limitations with the other two method preferred despite their drawbacks and lower precision percentages.**

Keywords-Appliance States; Load monitoring; Non-Intrusive Load Monitoring (NILM); Power Signatures; REDD

I. INTRODUCTION

Electrical energy is the most important and convenient source of energy related to the economy and people. In the last few decades, the electrical consumption has kept on rising at an alarming rate. With more technologies at our disposal to facilitate our daily tasks and the world population growing annually, the demand of electricity is increasing rendering it more and more challenging to meet such requirements.

A significant percentage of energy is used in household for different purposes: heating and cooling of premises, lighting and other electrical appliances. In 2017 in the European Union (EU), 27.2 % of total energy consumption was represented by households [1]. Saving energy has transitioned from an option to a necessity, due to limited amount of available resources, so as to meet current and future demand of energy consumption of the population. This may be achieved through efficient use of energy. A reduction in energy usage would result into the better protection of the globe since a decrease in demand requires less production of energy from non-renewable sources of energy. Therefore, it will lessen its negative impact on climate change and greenhouse effect on the environment.

It is impossible to deduce which electrical devices have an important contribution in the consumption of the total electricity bill due to the increasing number of household electrical appliances. Thus, people are unable to diminish their consumption as they are unaware of the factors impacting on their total electricity demand. Studies have shown that providing consumers with real-time power consumption information, at the aggregate level, helps them to change their behaviour and save 10-15% on power costs [2-4].

Electrical load Identification is an approach used in order to disaggregate the total energy consumed in households during a certain period of time to detailed ones. It will help customers determine the kind of appliance, operating modes and consumption details of electrical devices. Normally, sensors acquire data on usage details of appliances such as power consumed, time and frequency of use for a limited period of time. The data are then transferred to a processing system for processing and storage from where it can be accessed and displayed anytime.

It is more practical and less costly to use a single sensor at the main meter instead of a sensor for each appliance for load identification. As a result, a simpler hardware network is obtained nevertheless requiring more complex algorithms for load identification. This approach is referred to as Non-Intrusive Load Monitoring and research on the latter was started in the 1980 by George W. Hart, Fred Schweppe and Ed Kern from Massachusetts Institute of Technology (MIT) for the purpose of measuring voltage and current data to determine the discrete states of electrical appliances [5]. For households, power consumption of appliances is the parameter used to record the usage of devices. This data however, can only reveal the overall energy consumption of the building and needs to undergo a number of processes to have a detailed decomposition of load for a defined period of time. Disaggregation techniques are used to decompose the consumed aggregated energy signal into detailed discrete loads in a building.

The main objective of this paper is to decompose the overall energy consumption into detailed energy consumed by each distinct appliance through the use of identification algorithms. The rest of the paper is structured as follows: Section II describes existing research and challenges in this field of work, Section III presents the framework considered for the design of the algorithms, and Section IV presents the simulation results and discussion before concluding the paper in section V.

II. NON-INTRUSIVE LOAD MONITORING SYSTEM

In this section, a review of the different types of existing Non-Intrusive Load Monitoring (NILM) system modelling is studied, especially how data is acquired, processed, outputted and how they vary from each other in their principles of operations.

A. Load Monitoring

Load Monitoring is the procedure of recognizing and gathering measurement of devices in a power system and is primarily used for the determination of the operating states of appliances to understand their distinct behaviour in a complete network [6]. Its main goal is to conserve the consumption of energy though proper timing of appliance activity, optimum usage and reducing unnecessary usage for minimizing unwanted energy consumption. As a result, it is possible to advise consumers of feasible savings in their total electricity bill by appropriate scheduling of their loads. Load monitoring helps investigate how loads behave individually in a complete and it can be classified as either Intrusive Load Monitoring (ILM) or Non-Intrusive Load Monitoring (NILM).

ILM is a standard metering network that records the energy consumption of an appliance's by attaching metering devices to each and every load in the building under interest. This type of monitoring is known as intrusive as the power meters require to be installed in the house. It necessitates huge costs due to complex installation and expensive maintenance of various measurement devices. Nonetheless, accurate results are obtained from this type of system.

NILM is a field of computational sustainability work, founded by George Hart with his research mainly concentrating on household appliances with the purpose to procure consumption data of the appliances without the necessity of monitoring at sub-level [5]. NILM is suitable for deducing the operating states and energy consumption of each appliance by analysing the measurement taken by the power meter attached to a building's main. It can be considered by viewing the mains circuit as an input while ignoring the lower level connection, to provide information on each appliance consumption details as an output. It is referred as non-intrusive since no intrusion into the building is required in this type of system [7].

B. Data Acquisition

The majority of NILM methods use data procured from the principle smart meter of the building only, but in reality, learning information from several individual smart energy meters are necessary. Data acquisition is a process of acquiring overall load data from a building at regular interval of time for extraction of features [8-9]. The energy meters estimate the Alternating Current (AC) basic parameters which include: voltage, ΔV (in Volts, V) and current, I (in Ampere, A) and are processed to generate real and reactive power.

Apparent power, S (in Volt-Ampere, VA) is the total transfer of energy due to reactive losses in a circuit while reactive power, Q (in Volt-Ampere-Reactive, VAR) quantifies the power dissipated by capacitive and inductive loads. Real power, P (in Watts, W) is the net transfer of energy irrespective of the path and is referred to as average power or simply power. Additionally, energy consumption (in Kilowatt-hour, kWh) is the quantity of power absorbed by loads during a period of time. Other important parameters are power factors (PF), electric properties, harmonic distortion, transients and electromagnetic interference (EMI) [10-11].

In order to extract required features from the recorded signals, it is fundamental to focus on the sampling rate and is normally classified into two main categories namely the high sampling rate (greater or equal to 1 Hz) and low sampling rate (less than 1 Hz). Sampling at a specific rate allows for extraction of features available only at these frequencies [9]. Load identification is feasible with the application of algorithms with familiar properties in the data of particular appliances.

C. Appliances States

Different appliances have disparate states of operation respective to their functioning or use. Four types of state can be identified [12]:

The single state appliance which consists of only 2 states namely On/Off describing that devices can only be either on or off. The single state has nearly a single power value whenever in use (On state) and zero power value otherwise (Off state).

The Multistate appliance has multiple operating states besides the On/Off state. Therefore, each of these states has a distinctive power value. These appliances different operating states switching pattern are distinct and repeatable making them easy to be recognized through the use of disaggregation algorithms.

Continuously Variable Devices (CVD) are appliances that don't have a specific amount of states due to their varying power property. Hence, such characteristics are quite difficult to disaggregate and therefore diminish considerably the accuracy of the system.

Some appliances are used constantly throughout days and weeks, thus remaining active with constant power consumption. As a result, these appliances are normally known as "permanent consumer devices" and devices like telephone sets and smoke detector belong to this classification.

The different types of operating states pattern [12] acts as an additional feature to discriminate between categories of disparate appliances. Researchers have focused on defining load signatures according to the listed categories for better identification accuracy.

D. Appliance Signature

Appliance signature is a specific and unique characteristic exhibited by electrical appliances during typical operating cycle. It may contain data concerning electrical parameters value in the course of transient states and steady states. This data allows appropriate monitoring and recognition of appliance from the household overall energy consumption measured. An original sample from Hart in 1992 depicts a power signal sample obtained from the main meter based on simultaneously switching of loads resulting into an aggregation energy signal of active appliances [12]. Du et al. stated that signatures used for load identification are typically classified into transient state signature and steady state signature [13].

1) Steady state features

Signatures consist mainly of two different types, transient and steady state. The latter is a signature type that makes use of steady state characteristics derived from appliance's steady state operation. Hart came up with the notion of NILM and the power change technique where the input signature utilized consist of the reactive power (Q) and the real power (P). The appliances are categorized by determining the variations of P and Q. Hart illustrated how dissimilar power signatures are produced by distinct electrical devices upon operation. This method is advantageous in the sense that low sampling datasets can be used and how simple appliances consuming high power can be recognized. Howbeit, it is strenuous to devices having several operating states and appliances consuming low power or approximately similar power [5]. The fluctuations in power are compared with predefined database for load identification via the location in the P-Q plane.

Figueiredo et al. and Najmeddine et al. made use of the current (I) and the voltage (V) as the signature. They extracted attributes like the Root Mean Square (RMS) and peaks of the current which are appropriate for classification except for multistate and continuously variable appliances. At high sampling rate, harmonic signatures of current can be extracted from data. Various investigations are being conducted on the acquisition of harmonics through Fourier series. Single state appliances and "Permanent Consumer Devices" are effectively categorized by means of current harmonics however requiring all the combinations of the harmonics dataset of the electrical devices. As a result, in practical, it proves to be exorbitant for an escalating number of appliances [14-16].

Lam et al. suggested the classification of appliances on the basis of the form of V-I direction and manage to classify them into eight categories with high precision [17]. Gupta et al. examined the effectiveness of identification based on the noise originated by the running of the appliance. Nonetheless, noise is susceptible in the environment resulting in low efficiency. Moreover, additional equipment are required for measuring the noise rendering it not suitable for practical use [18].

2) Transient state features

The Transient state is a type of signature that has lower overlapping in contrast to steady state signatures. Nonetheless, a weighty drawback is that high rate of sampling is needed to measure the transients present in the signal. Chang et al. suggested that the power consumed when an appliance is switched on can be considered as a signature and after a few years, discovered the transient physical response of power through the use of wavelet transform [19-20]. The latter is a frequency analysis approach when used to study transient signals, it generates frequency domain data together with its respective location [21]. Leeb et al. presented a classification technique that analyzes the spectral envelope through the use of Short Time Fourier Transform (STFT). This method is suitable for identification except for type 4 appliances [22].

Cole and Albicki utilized power spikes produced from transition [23] while Norford and Leeb proposed that the transient data pattern can be used as a property [22]. Using current transient for recognition is suitable only for type 1 and 2 loads. Transient power is a property that can be used for load identification since most devices have repeatable transition patterns. This type of method requires constant supervision and sampling at high rate [15].

Patel et al. extracted the voltage noise from the transient response and sampled it to define three kinds of noise namely steady-state continuous noise, on/off transient noise and steady-state line voltage noise. Howbeit, this technique requires an understanding of power flow including of active power, reactive power and voltage phase respective to current [24].

3) Other features

Current harmonics generated by load can be utilized as a feature for appliance recognition. A linear model states that the current response is directly correlated with the voltage pattern thereby having the same type of signal. Various electrical devices produce significant current at high frequencies. Almost all loads generate merged harmonic currents except for incandescent lights and resistive heaters. Appliances having virtually the same real and reactive power may be distinguishable using harmonic current signatures [25].

Fundamental Frequency Signature is a type of signature which is obtained from the measurement of the power, current or the overall load admittance. The step change in these parameters is considered as signatures. Essentially, events data are obtained from variations by overall load. Therefore, the changes in the consumed power generate a non-ideal signature due to practical reasons of the appliance and as a result, admittance is more suitable in contrast to power and current to be used as a parameter for signature. For a linear device, admittance relies on its voltage and for appliances connected in parallel, the admittance is additive.

In NILM network, the output from data acquisition stage is a finite-duration signal and Discrete Fourier Transform (DFT) allows the determination of the spectrum of such type of signal via the decomposition of successive values into elements of dissimilar frequencies. For a finite-duration sequence x[n] given in (2), the DFT of the signal can be computed using (1).

$$\mathrm{X(k)} = \sum_{n=0}^{N-1} \mathrm{x(n)} e^{-j\frac{2\pi}{N}kn}. \tag{1}$$

And the Inverse Discrete Fourier Transform (IDFT) can be computed using:

$$\mathrm{x(n)} = \frac{1}{N} \sum_{k=0}^{N-1} \mathrm{X(k)} e^{j\frac{2\pi}{N}kn}. \tag{2}$$

The main peak can be derived from (1) at *k=0* for each set of finite duration sequence x[n]. However, in practice, its computation speed is low due to high complexity calculations involved. In 1965, computer technologists James Cooley and John Tukey, proposed the Fast Fourier Transform (FFT) algorithm that decreased the DFT calculations complexity from order $O(N^2)$ to O(Nlog(N)) where N is the data size [26].

4) Intelligent learning

The decomposition of the load can be processed in either a supervised or unsupervised manner. The latter uses predefined building models for classification of the appliances while the former uses clustering methods to identify the appliance. Although supervised methods usually having better accuracy, unsupervised methods are preferred for commercial buildings since it proves to be much less complex and expensive.

In comparison to other methods, Artificial Neural Network (ANN) is manipulated to learn particular features of various loads known as the training process. ANN possesses the ability to hold any kind of information and to handle synchronously multiple load states, unrequired comprehension of device behaviour, the flexibility of the system with respect to higher amount of appliances and types of data and an automated learning process via profiling sensors and user error feedback [27].

K-nearest neighbour (KNN) is a classification method normally applied after disaggregation of signal. This algorithm was tested on pre-processed REDD dataset to evaluate its performance by verifying whether aggregated energy consumption signature is distinguishable or not. It was concluded that it had a high efficiency in identifying electrical appliances like furnace, microwave, oven, washer dryer and kitchen outlet. However, it was incompetent in the case of electronic device signals [28].

E. Datasets

The incertitude encircling the precision of methods has instigated several high grade datasets of appliances power signatures to be made available to the public. The MIT REDD [29] and Carnegie Mellon University (CMU) Building-Level fully labelled Electricity Disaggregation (BLUED) [30] provides data especially for household load disaggregation while the UMass Smart Home data [31] is not suitable for NILM evaluation. Additionally, Green Button has several public dataset which is nevertheless, available only upon application to the company [32]. In this work, REDD is chosen to be used since it is deemed as the most suitable dataset for use.

The REDD is a public dataset designed for the sole purpose of energy disaggregation and represents the biggest dataset available to public using measurements from 6 distinct houses. REDD comprises of real-time load electrical consumption for several households over various months' period. From each house, the current and voltage from every single circuit and chosen plugs is recorded and stored to the central database.

A wireless plug monitoring network (Enmetric router and Power Port, invented by Enmetric System, Inc.) used to measure plug-level data. The appliances are plugged into the power strips and the router transmits the data via Dynamic Host Configuration Protocol (DHCP) server. For circuit level data, the eMonitor (invented by Powerhouse Dynamics, Inc.) has Current Transformers (CTs) attached to each distinct circuit in the building's circuit breaker, uses its Application Program Interface (API) to relay power consumption to a central server at the highest rate possible. A Pico TA041 oscilloscope probe is used to record the voltage in the house, CTs from The Energy Detective (TED) to record current in the power mains and a National Instruments NI-9239 Analog to Digital Converter (ADC) to convert analog signals to digital data. These data are stored to the software system on a laptop that transfers processed information to the central database which incorporates a web interface that displays real-time data to users.

REDD collected data at 15 KHz which is the highest frequency suitable of storing the information since data measured at high frequency can be re-sampled to obtain lower frequency data. Normally, the samples used for disaggregation consists of a sampling rate of 1 Hz or data is recorded every 3 seconds in some cases [29].

F. Challenges

The major obstacles in Electrical load identification are mostly due to the following which have been encountered in other types of systems:

- Networks are unable to differentiate between loads having similar energy consumption.
- The systems don't possess the ability to identify loads irrespective of their number of operating modes and differentiate among such states.
- The systems are unable to decompose the overall power consumption into detail individual load activity. Thus, they are not able to recognize appliances operating in parallel.
- The systems are not flexible to disturbances due to outer elements (unprofiled appliances).
- The systems are unable to deal with loads having lengthy operating cycles.
- Appliance profile recognition can be disrupted due to power factor correction by the energy supplier at the substation level.
- The systems are unable to decompose the aggregated power signal into detailed individual power signal thus providing the power consumed by each appliance upon activation.

III. METHODOLOGY

In this work, several identification techniques are implemented to analyze their effectiveness on the recognition of appliances. A survey is also conducted to determine the different patterns of power consumption and the types of appliance used by contrasting age groups. Daily samples generated for testing are based on the energy consumption pattern obtained from the survey.

A. Hardware and Software Requirements

The software selected for use in this work is the MATLAB R2015a which is a high-level language normally used for numerical calculation, visualization and improvement of application. The software installed requires any Intel or Advanced Micro Devices (AMD) x86 processor supporting Streaming Single Instruction Multiple Data (SIMD) Extensions 2 (SSE2) instruction set and needs a disk space of 3-4 GB for a typical installation. Moreover, it requires a minimum Random Access Memory (RAM) capacity of 2 GB while a hardware accelerated graphics card supporting Open Graphics Library (OpenGL) 3.3 with Integrated Genome Browser (IGB) Graphic Processing Unit (GPU) memory is recommended [33]. The laptop used for the implementation and simulation of the algorithms is an Intel Core i5 with a 2.30 GHz processing speed, an installed RAM capacity of 8 GB, incorporating a system type of 64-bit Operating System and a Windows 7 Ultimate edition.

B. Selected Appliances

For implementation and simulation purposes, four appliances are chosen from the REDD system based on their different kinds of power signatures which are dissimilar from each other and they are the following listed below. The power signatures from the REDD system are unprofiled and therefore contain mostly of small variations and few large variations which may be due to internal or external factors to the appliance upon measurement. The power signatures have been estimated as far as possible to match those obtained from the REDD system in order to use them to test the efficiency of the algorithms implemented. The following appliances have been chosen for use [29]:

- *Refrigerator*
- *Microwave*
- *Furnace*
- *Oven*

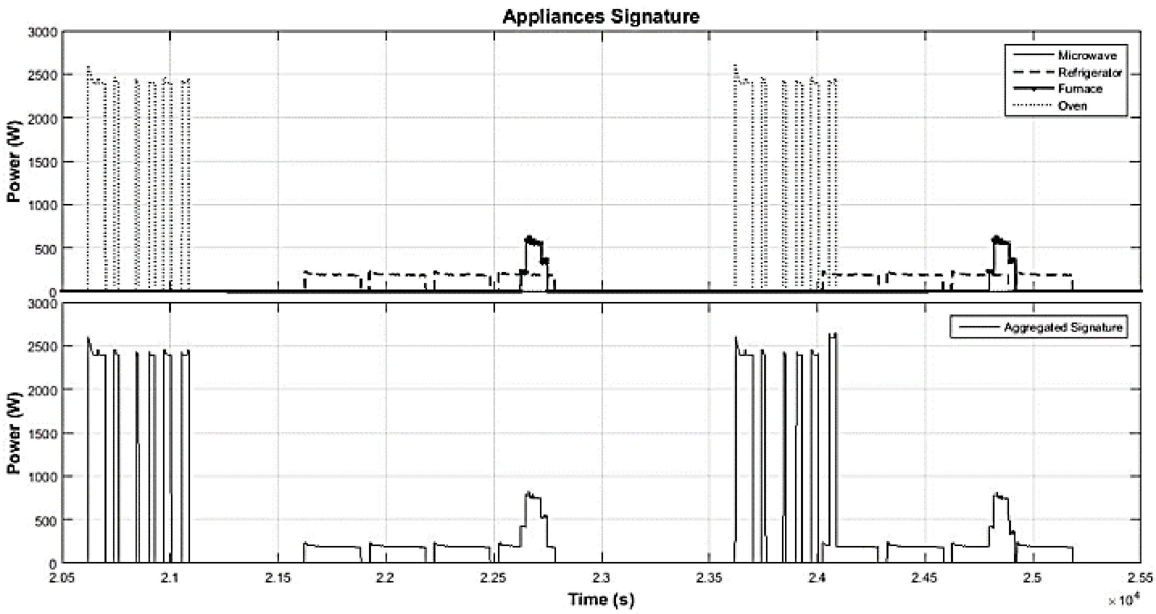
C. Justification for Choice of samples

The data obtained from REDD is the power signature of individual appliances and 6 aggregated power signal samples corresponding to 6 different houses which comprises of the power consumption of 12 distinct appliances [29]. Hence, these aggregated signals are not suitable for use in this work since only 4 loads from REDD are chosen for simulation purposes. As a result, the power signatures of the individual loads are used to generate various sets of aggregated signal samples comprising of only the chosen appliances for simulation purposes.

D. Data Collection

A survey has been conducted that amasses a wide range of public opinions on electricity and electrical appliances as the main topic to people belonging of different age groups. This was carried out with the prime purpose to ascertain how determinate the public is towards saving electrical energy and the factors encouraging or limiting people contributing to it. Moreover, it intends to perceive how frequently people use common electrical devices in their routine lives in conjunction with their respective time of use. The results of the survey conducted are based on the response of 36 people who have participated. The results depict the normal usage pattern of electrical appliances by the participants in their daily activities and their corresponding average typical frequency of use per day. Howbeit, in this work, only the electrical energy consumption patterns of the 4 chosen loads are taken into consideration and are thus used to formulate the daily power consumption samples to be used for simulation purposes of the different algorithms. Fig. 1 illustrates a small portion of the aggregated power signature sample for an entire day generated using the chosen appliances.

Figure 1. Individual and aggregated power sample



E. Assumptions made

- Only one appliance per type is assumed to be available within a single household and therefore, the power signature of an electrical device cannot be superimposed with itself.
- All appliances are assumed to have repeatable signature for each use with fixed duration.
- An appliance may be detected more than once within a single operating period.

It is assumed that an appliance does not consume any power when it is not in use. Therefore, the aggregated power signature would account to a power level of zero when all loads are switched off.

F. Identification Algorithms

Each appliance power signature contains its particular properties such as active & reactive power rating, duty cycle, the amount of rising or falling edge, and the harmonic frequencies that are distinct respectively [34]. Howbeit, as with all techniques, there is no guarantee that the signal will be flawlessly disaggregated. Hence, each dataset of signature must be individually analyzed empirically. In each method, disparate sets of features are considered and extracted which are then used for the disaggregation of the overall signal before analyzing each feature for the identifying the respective loads. In order to decompose the aggregated signature, 3 identification algorithms are chosen to be implemented, each analyzing dissimilar features of the signal. This will help evaluate the weaknesses present in each method and would depict the type of features most suitable to be analyzed. The properties examined for each method and the implementation processes are further described correspondingly below.

1) Load Switching Transient (LST) Analysis

The signatures obtained from the REDD system represent the power consumption of the appliances. This technique detects any ON/OFF transition occurring in the sample of data used. Whenever an appliance is switched on, it undergoes a transition, also referred to as a Turn-On transition, since it starts to consume electricity. It is also the case when the device is switched off thereby ceases consuming electricity and the resulting transition is known as the Turn-Off transition.

Some appliances possess operating states consisting of multiple triggering and as a result, multiple transitions occur which may be superimposed with the transition of other device being switched. Hence, all transitions are considered with the purpose to identify activations and deactivations of appliances. This bestows an advantage over techniques considering either only Turn-On or Turn-Off transients in the case that if any of the transient passes undetected due to some limitations, it can be recognized by the other.

The transient data extracted is the step-change of power (ΔP) in the signature and it normally corresponds to the power required by the load to switch on or off. Ideally, the small fluctuations present in the power signal are assumed to be negligible. An optimization technique is also implemented which include a set of predefined ΔP of distinct and combinations of loads that may be due to individual or simultaneous operation. The step changes obtained from the Turn-On and Turn-Off transients are passed through the optimization algorithm in which they are compared with the existing set of data and the difference respective to each single data is recorded. Then, the optimum solution having the least error value, that is, the value nearest to the calculated one is chosen. Hence, the appliance in use is identified based on the selected value. The block diagram of the LST algorithm and the flowchart are given in Fig. 2 and Fig. 3 respectively.

Figure 2. Block diagram representation of LST Algorithm

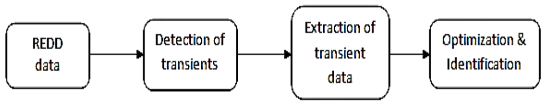
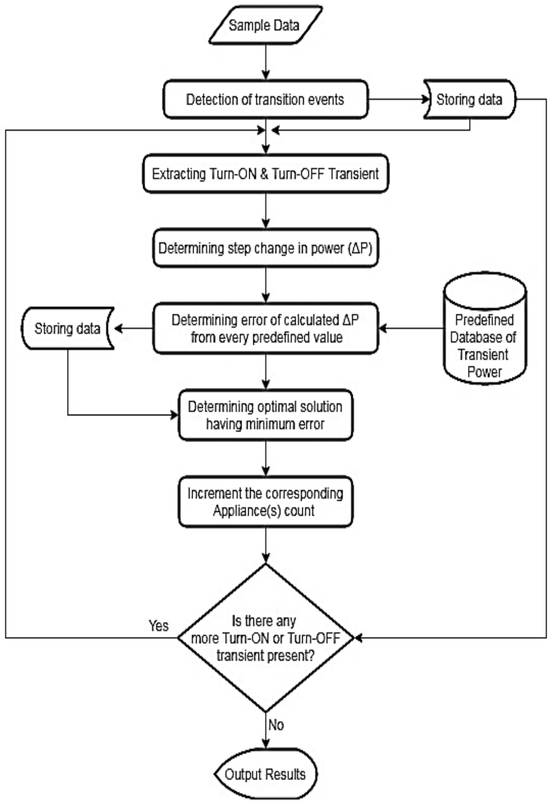


Figure 3. Flowchart representation of LST Algorithm



2) *Mean Steady State (MSS) Analysis*

This method analyzes the steady states occurring in the sample data. Whenever an appliance is switched on, it undergoes a turn-on transition before reaching a steady state of operation and ends when another switching transition occurs. Ideally, the steady state of a load comprises of a constant power being consumed with no fluctuations materializing. Practically, in the steady state, the appliance consumes approximately the same amount of power with small variations, that is, there is no major change in the power consumed throughout this state.

Appliances possessing different operating states with distinct power consumption are classified as per their operating modes accordingly. The steady state data extracted is the amount of power being consumed with respect to the operating mode. The variations present in the data may be due to internal or external factors of the load. The mean of the steady state is determined to have an approximate power level consumption of the appliance's different modes of operation.

An optimization technique is also implemented which include a set of predefined steady state values corresponding to distinct and combinations of loads that may be due to individual or simultaneous operation. The mean values obtained from the steady state are passed through the optimization algorithm in which they are compared with the existing set of data and the difference respective to each single data is recorded. Then, the optimum solution having the least error value, that is, the value nearest to the calculated one is chosen and the appliance in use is identified based on the selected value. The block diagram of the MSS algorithm and the flowchart are given in Fig. 4 and Fig. 5 respectively.

Figure 4. Block diagram representation of MSS Algorithm

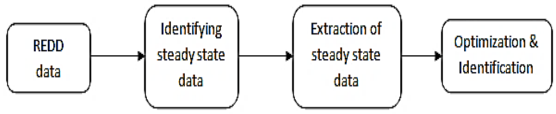
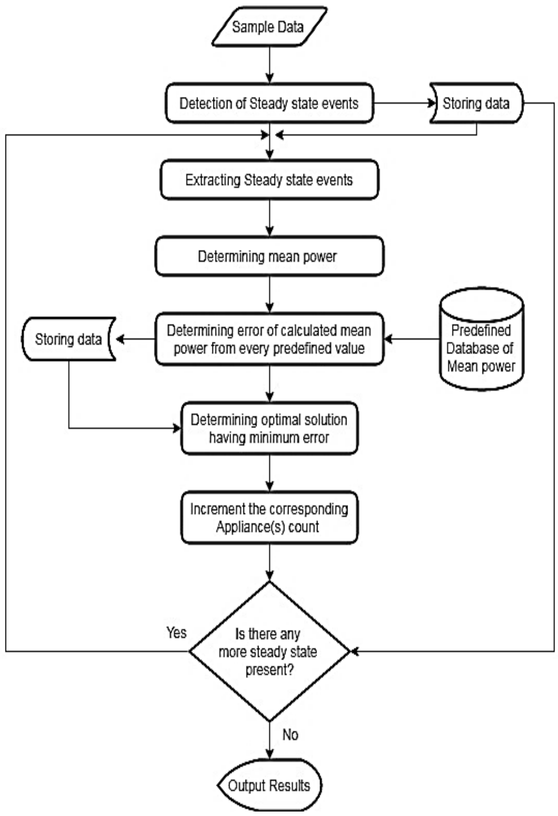


Figure 5. Flowchart representation of MSS Algorithm



3) *Discrete Fourier Transform (DFT) Analysis*

In this technique, the aggregated signal obtained is sectioned into several parts classified by two different categories namely the active and inactive group. Whenever one or more appliances are in use for a period of time, it is classified as active while the contrary is true for the other group, that is, when no appliance is operating during a certain amount of time.

After the entire signal has been sectioned, only the active parts of the aggregated signature are taken into consideration and extracted for further processing. Hence, the data obtained is transformed into the frequency domain through the use of DFT equations. However, the Fast Fourier Transform (FFT) tool is used for faster calculation, thus requiring less processing speed. In the frequency domain, the main peak obtained represents the power of the signal and can be determined individually for each region using (1) at frequency index $k=0$. This value may correspond either to a single load or to several loads operating in parallel.

An optimization technique is also embedded in this algorithm which is used to identify the optimum solution. It includes a predefined set of main peak values corresponding either to distinct appliance or to a combination of them. The calculated values are fed into the optimization algorithm in which they are compared with the predefined DFT set of data consisting of individual and different combination of load and the difference respective to each single data is recorded. The optimum solution having the least error value, that is, the value nearest to the calculated one is chosen and the corresponding appliance is identified based on the selected value. The block diagram of the DFT algorithm and the flowchart are given in Fig. 6 and Fig. 7 respectively.

Figure 6. Block diagram representation of DFT Algorithm

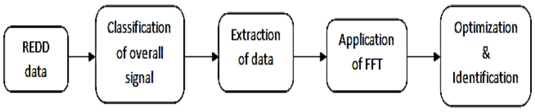
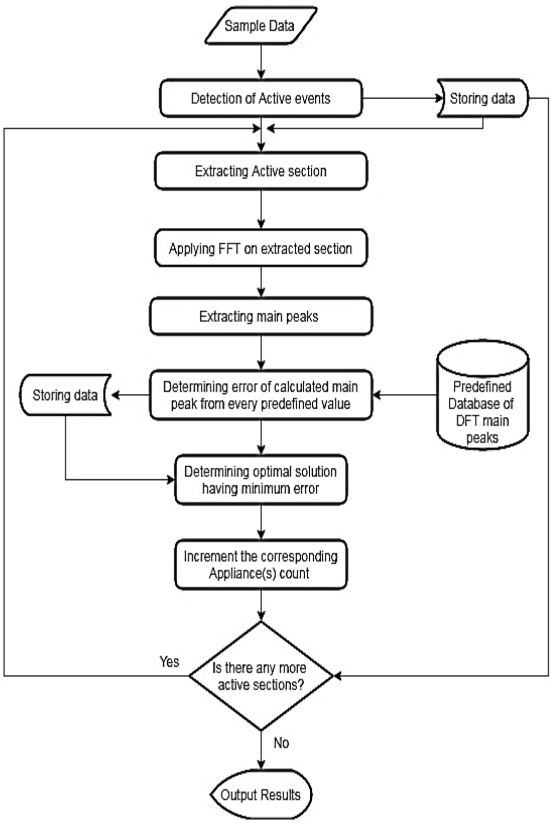


Figure 7. Flowchart representation of DFT Algorithm



IV. Results and Discussion

This section presents the results obtained in correlation with the method based on the samples used. Each algorithm is analyzed based on its outcome and the performances are evaluated. The accuracy of each algorithm of each method is determined using (3).

$$Accuracy = \frac{Number\ of\ Correct\ Identifications}{Total\ number\ of\ Expected\ Usage} \tag{3}$$

A. Simulation Results

The simulation results of all samples for the LST, MSS and DFT algorithms are given in Table I, II and III respectively.

TABLE I. LST SIMULATION RESULTS OF ALL SAMPLES

Appliances	**Accuracy (%)**		
	Turn-On	**Turn-Off**	**Overall**
Refrigerator	100	100	100
Microwave	97.6	100	98.8
Oven	100	99.6	99.8
Furnace state 1	97.2	-	97.2
Furnace state 2	100	100	100
Furnace state 3	-	100	100
Total	99.7	99.8	99.8

TABLE II. MSS SIMULATION RESULTS OF ALL SAMPLES

Appliances	**Accuracy (%)**
Refrigerator	96.8
Microwave	100
Oven	98.9
Furnace state 1	95.3
Furnace state 2	94.8
Furnace state 3	91.8
Total	97.1

TABLE III. DFT SIMULATION RESULTS OF ALL SAMPLES

Appliances	**Accuracy (%)**
Refrigerator	100
Microwave	100
Oven	100
Furnace	100
Total	100

B. Discussion

1) Load Switching Transient (LST)

In this method, appliances are recognized with respect to their Turn-On and Turn-Off transients. As desired, these transients were extracted and compared to predefined set of values to identify the respective loads in use at specific times. This was executed for several distinct samples and the results were tabulated.

From the results obtained, it can be deduced that the algorithm has an accuracy of 99.7% on the Turn-On transients accounting to 652 correct identification over a possible of 654 while it has a precision of 99.8% on the Turn-Off transients amounting to 653 correct identification over a total of 654. These percentages depicts the limitation of this technique, which is the overlapping of significant positive and negative transients of load switching generating an entirely different value that may correspond to other appliances or a combination of them. Howbeit, it is an extremely rare scenario since sampling is done in seconds and it depends on the quantity of appliances in the house, frequency of use and the number of people using loads simultaneously. In this study, this type of scenario occurred with a probability of 0.153% and hence, this algorithm may effectuate higher identification accuracy if this probability decreases.

Moreover, large variations in the operating power of an appliance superimposing with the transient of other loads generates different net power level, thus resulting in incorrect identification of loads having nearly similar Turn-On or Turn-Off transient power.

Nevertheless, even if one transient of a load is not incorrectly recognized due to the limitations mentioned above, the appliance can be identified through the other transient present in its power signature signal. In practice, the occurrence of having both transients affected by such cases is of a tremendously low probability. In addition, the algorithm is independent of the usage duration of the appliance and is therefore suitable for use. Furthermore, the exact activation and deactivation time of appliances can be determined and as a result, the operation duration of the loads may be deduced.

2) *Mean Steady State (MSS)*

In this technique, the steady state of the aggregated signal is analyzed to determine the overall mean power consumption. These data are extracted and compared to predefined set of values to identify the respective loads in use at specific times. This was executed for several distinct samples and the results were tabulated.

The aggregated power signature may have various steady states during a single active region due to the switching of several appliances. Hence, even a single state appliance may have more than one steady state power level in the signal within a single activation period due to it either operating alone or with multiple loads operating simultaneously.

Based on acquired results, the algorithm has an overall precision of 97.1% accounting for 974 correct recognitions of appliances over a total expected amount of 1003. The 2.9% of inaccuracy is mainly due to appliances, such as the refrigerator and the oven, that have continuously varying power level throughout their steady state. This hinders the algorithm from correctly identifying devices since the mean power calculated is dependent on the number of values considered for such type of loads. Thus, for such appliances, if only the first few data values are taken into consideration, the mean power would correspond to other load or a combination of them. In this method, appliance possessing continuously variable signature is correctly recognized when they are operating alone either during its entire activation period or for a specific duration depending on its power signature. Moreover, the algorithm requires 2 or more values to determine the mean and ignores single point data caused by successive transitions.

Despite its limitations, it still generates a high accuracy percentage for the set of appliance and samples used. However, this method is most suitable for use when appliances possessing continuously variable signature are not considered and where they have dissimilar power consumption level thereby generating better accuracy.

3) *Discrete Fourier Transform (DFT)*

In this method, all transients and steady state values within an active section are taken into account since the main peak extracted is the summation of all power consumed in that time interval. These data are compared to predefined set of values to identify the respective loads in use at specific times. This was executed for several distinct samples and the results were tabulated.

From the results achieved, it can be observed that the algorithm has an accuracy of 100% which represents 428 correct identification over a totality of 428. However, this technique has some limitations which has not been encountered in the set of samples used, thus having a perfect precision. For simulation purposes, the power signatures are considered as repeatable which may not be the case in practice. In real-time, the operating duration is not nearly constant for several appliances and their power level is subjected to different variations for each usage. Thus, the main peak obtained from this algorithm would largely defer from the predefined value since it is highly sensitive on the operating period and power consumption level. For instance, if only the microwave is considered and operates for an additional 5 seconds, an increase of approximately 8725 W would be notable in the main peak extracted. As a result, it would correspond to other appliances or a combination of them. Additionally, phantom loads may also contribute to a significant increase in the main peak over a long active region.

Hence, in practical, this technique is not suitable for use as it may generate a very low accuracy percentage due to significant variations in the appliances' operation time and power consumption level. However, it may be hybridized with other algorithm to impart some of its features and thus, boosting their identification precision.

V. Conclusion

In this work, three NILM techniques are proposed namely the Load Switching Transient (LST) that identifies appliances at every Turn-On or Turn-Off instant, Mean of Steady State (MSS) which identifies devices at every significant distinct power level found between transients and the Discrete Fourier Transform (DFT) that identifies loads within each active region. All three methods were able to recognize the appliances from the aggregated power signature samples with an overall precision of 99.8%, 97.1% and 100% respectively.

However, even though the DFT algorithm has a perfect accuracy in this work, it is not suitable for use in practice due to major limitations such as uneven operation period and different fluctuations in power consumption level of appliances upon distinct usage. Furthermore, is unable to differentiate among the multiple modes of operation of an appliance. Despite the drawbacks of LST and MSS algorithm identified, they can be implemented and adapted for use in real time recognition while possessing high accuracy.

It is more appropriate to use the LST algorithm since it is less susceptible by external factors and more reliable among all the techniques implemented. Moreover, the exact activation and deactivation time of appliances can be determined and as a result, the operation duration of the loads may be deduced.

In this work, the various effects of different appliances on the aggregated signal have been observed as well as diverse load power signature from REDD were analyzed and from the latter, several samples were generated. Finally, based on the simulation results obtained, it can be observed that the algorithms implemented overcome various challenges present in energy disaggregation systems such as identifying multiple operation states, simultaneous appliances activities and distinguishing between loads having similar power consumption. Moreover, the algorithms are able to cope with lengthy samples while providing partial information on detailed appliance consumptions.

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