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Non-Intrusive Load Monitoring Techniques for Energy Disaggregation: A Survey

C. Shanmugha Priya[1], Dr. M.P Rajakumar[2]

Assistant Professor, St.Joseph's College of Engineering, Chennai, Tamilnadu, India[1]

Associate Professor, Dept. of CSE, St.Joseph's College of Engineering, Chennai, Tamilnadu, India[2]

ABSTRACT:Appliance Load Monitoring (ALM) is a must for all energy saving solutions, and also to obtain appliance-specific energy consumption patterns that could be used for optimal energy utilization. Hence, it is essential to identify the appliances that run in a residence at a particular instant of time. Energy monitoring can be done by attaching energy power meter on every device of interest; however it incurs high cost and installation complexity. Non-Intrusive Load Monitoring (NILM) is an algorithm that can disaggregate a residential power usage into power running across each appliance. NILM is a better option for energy disaggregation, as it can disaggregate devices from the aggregated data obtained from a single energy meter. This paper provides an overview of Non-Intrusive Load Monitoring System and various techniques used for energy disaggregation. This paper reviews the various disaggregation algorithms used for appliance recognition and thereby highlight their challenges and future research direction.

KEYWORDS: Intrusive load monitoring; Non-Intrusive load monitoring; Load signatures; Disaggregation algorithms. Energy management

I.INTRODUCTION

Today, energy conservation and energy management are challenging issues due to tremendously increasing energy demands. Researchers are working hard to develop a low cost technology in order to find solution to the problem. Researchers mainly focus on energy consumption through reduction in the energy wastage through continuous load monitoring of appliances also known as Appliance Load Monitoring (ALM). Motivated by this approach a large scale deployment of smart meters took place in many residential environments but the associated cost and inconvenience to be used were the prime reasons that smart meters were not a better approach for energy disaggregation.

Researchers proposed non-intrusive methods as an attractive alternative approach with reduced manual overheads and cost. Motivated by this, this paper provides a comprehensive discussion on the different types of appliance signatures and load identification algorithms used in NILM for energy disaggregation.

The remainder section of the paper is organized as follows. In the next section, this paper providing an overview of the NILM framework, whereas different types of appliance features used for energy disaggregation is discussed in Section III. In Section IV survey on load recognition techniques being applied in NILM is presented and section V lists the different load monitoring strategies practiced. Section 6 is the conclusion part.

II. OVERVIEW OF NILM FRAMEWORK

The concept of NILM is it is a method for disaggregating electrical loads from the aggregated load data by monitoring the appliance specific power consumption patterns. The aggregated power data is obtained through an electric meter which is outside the residence and hence this method is referred as non-intrusive since this method does not require any equipment to be connected inside the residence. This problem could be formulated as follows: the aggregated power signal is denoted as P(t)and the formula is mathematically represented in Eq. (1),

$$P(t) = p_1(t) + p_2(t) + ... + p_n(t) \qquad (1)$$

where n is the total number of appliances within the time period t and p_i is the power consumption of individual appliances contributing to the aggregated power data. The goal is to decompose the aggregated power P(t) into

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individual appliance signal. Disaggregation mainly depends on appliance signatures. Appliances Signatures are further characterized by appliance category. Appliances are classified on the basis of their operational states as follows:

- **Type-I.** These are the appliances with two states of operation (ON/OFF). Examples include tube light, toaster, etc.
- **Type-II.** These are appliances with a finite number of operating states. Consumer appliances belonging to this category includes fan, stove burner etc.
- **Type-III.** These appliances are referred as Continuously Variable Devices (CVD) because of their variable power drawing characteristics with variable number of states. Examples of continuously variable devices include dimmer lights and power driller.
- **Type-IV.** These devices consume energy at a constant rate also known as "permanent consumer devices". Example devices include cable TV receivers, telephone sets.

The general framework of NILM approach is shown below in Fig. 1.

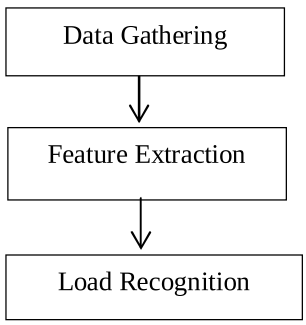

Figure.1General Framework of NILM

The modules starting from data gathering to appliance identification that define a general NILM framework as shown in Fig. 1 are discussed below.

Data Gathering Phase

The role of the data gathering module is to obtain aggregated load at an appropriate sampling rate in order to identify distinct load patterns. There are different types of power meters designed which can be further classified as follows.

Low-Frequency Energy Meters

There are different types of meters of different sampling rates available in the market. Sampling rate plays a major role in extraction of signals. For capturing higher order harmonics of electrical signals, sampling rate should satisfy Nyquist–Shannon sampling criteria.

High-Frequency Energy Meters

In order to acquire the transient events or the electrical noise produced by appliances, energy meters of sampling rate 10 to 100 MHz should be used. High frequency energy meters are quite expensive because of their sophisticated components and are designed specifically for the type of features that needs to be captured from the signal.

The data acquisition for NILM can further be classified into aggregated and circuit level data. A typical NILM system usually use of aggregate data acquired from a single meter. But there exists a challenge in this approach which is recognition of variable and low-power appliances along with high-power loads are quite difficult. A circuit-level approach has been proposed by [1] since it is often the case that high-power appliances usually have a dedicated circuit within homes and also there exists fewer devices on a circuit opposed to the aggregated NILM.

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Feature Extraction Phase

The next step after the data acquisition is to perform event detection. Events are caused by change in the ON/OFF of different appliances. These events can be defined in terms of transient or steady-state changes. Steady state methods recognize devices based on difference in their steady state patterns. The transient methods utilize transient patterns that distinctly define appliance pattern by capturing features like duration, shape and size of the transient waveforms [2].

Appliance Recognition Phase

After extraction of appliance features they have to go through load identification algorithms in order to recognize appliance-specific patterns from the aggregated load. For Appliance recognition most researchers used supervised learning approach that uses labeled data to train the classifier. Most supervised learning techniques adapted are either pattern recognition or optimization based. Optimization based technique matches the aggregated power measurements P(t) to all the possible combination of appliance power measurements which is already collected in a database to mitigate the matching error as mentioned in [2- 4].

But the drawback is when there exists unknown loads in the aggregated power P(t) hardens the optimization approach. Therefore pattern recognition technique is the most preferred option by researchers in order recognize load. Pattern recognition like pattern matching matches the captured features with a collection of appliance signatures already present in the load feature database so as to identify an event related to the operation of a load. Both approaches require training data which is a major drawback in the adoption of the approaches for the task of appliance recognition.

Researchers have also made use of unsupervised learning approaches but it still had an obstacle of requiring unlabeled training data. Recently, Researchers have focused on Graph signal processing based NILM approach for supervised learning where the events are represented by nodes of a graph and a graph signal processing based data classifier searches for a smooth graph signal under known label conditions for performing appliance recognition.

Researchers have followed different approaches to perform non-intrusive load monitoring. They differ by the below mentioned factors.

- Appliance feature used for monitoring
- The appliance recognition algorithm used for disaggregation
- Load monitoring strategy employed

III. SURVEY OF NILM TECHNIQUES BASED ON APPLIANCE FEATURES

The appliance features used for energy disaggregation used could be steady, transient or non-traditional features. Steady state feature could be classified as below in Fig. 2.

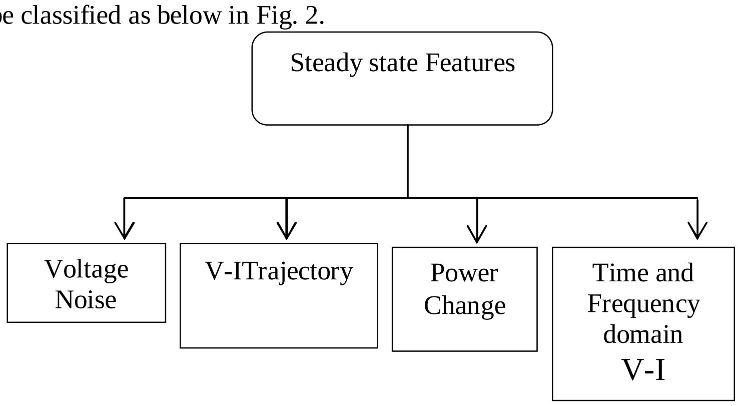

Figure.2Taxonomy of Steady State Signatures

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Transient state feature could be classified as below in Fig. 3.

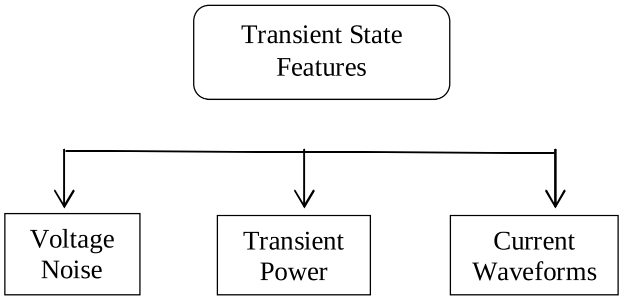

Figure.3Taxonomy of Transient State Signatures

NILM Methods using Steady State Feature

The NILM methods based on steady-state analysis utilize of steady-state operation of the appliance as features. Real power and Reactive power are prominently used steady state signatures for energy disaggregation [5] of ON/OFF or type I appliances. Real power is defined as the amount of energy taken by an appliance when it is operating. Reactive power is the energy which is already stored and released by inductors and capacitors of the appliances. Researchers [6-8] have tried to recognize load using real power as the only feature and identified that appliances with high power and distinct power drawing characteristics were easily recognized. But this approach fails for appliances with same power drawing characteristics. In order to mitigate this issue, researchers have used both reactive power and real power change [5, 9] through which type-I and few type-II appliances were recognized. But this approach also has a drawback of disaggregation that overlap in the real and active feature space mainly the low-power loads.

Because of the limitations of power based methods, researchers [10-12] tried different approaches using current I and the voltage V waveforms which captured distinct features such as Root Mean Square (RMS) and peak current and voltage values, power factor (PF) and phase difference. However, these approaches do not cover type-III appliances.

TABLE 1. Steady State NILM Methods

Steady State NILM Methods	**Appliance Features**	**Pros**	**Cons**
Voltage Noise [18,15]	EMI patterns	Simultaneous events and SMPS appliances could be easily detected	Only appliances with SMPS could be detected
V-I Trajectory [16,17]	Looping direction, asymmetry and area of V-I trajectory	Taxonomy of appliances could be built because of unique V-I curves	Low power appliances could not be detected
V-I waveforms [3,10]	Power factor, RMS	Resistive and inductive loads can be detected	Requires high sampling rate
Power change [5,1,6]	Real and Reactive power	Requires low sampling rate	Detects only type-I appliance

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Another approach was using current harmonics which can distinctly detect non-linear loads which consumes non-sinusoidal current during its operation. Real and active power together with harmonic features [13, 14] is used but harmonic analysis need high sampling rate and needs distinct harmonic signatures.

Gupta et al. [15] proposed an interesting approach in utilizing steady-state voltage noise an appliance would produce on its operation. But it needs sophisticated hardware for monitoring. V-I trajectory [16, 17] was proposed to detect group of appliances. It has been observed that V-I based approach is more efficient in classifying appliances because of their unique V-I curves.

3.2 NILM Methods using Transient State Feature

The transient feature is unique but the major challenging issue this feature could be extracted only at a high sampling rate [12]. Norford and Leeb [6] captured the shape of transient events and used that to perform appliance detection. Chang et al. [19] utilized “turn on” transient events disaggregate appliances. In [20], power spikes or overshoots occurring at the transitional stage were used. This method of disaggregation is effective but requires repeatable transient pattern and high sampling rate to capture such patterns.

In [21, 22] spectral envelopes of waveforms, real power and reactive power were used to increase the performance of disaggregation. But this approach fails in the presence of unknown loads. In order to obtain transient behaviour of appliances wavelet transform were used [23].Patel et al. [18, 24] captures voltage noise which comes along with the transient events. These noises are obtained from any electrical outlet inside the home. But these noises are appliance specific and require high sampling rate.

TABLE 2. Transient State NILM Methods

Transient State NILM Methods	Appliance Features	Pros	Cons
Voltage Noise (High Frequency) [18,24]	Noise Fast Fourier Transform	Appliances with Switch Mode Power Supply and multistate appliances could be detected	Noise are specific to each appliance
Transient Power [2,25-27]	Spectral envelopes and transient profile	Detection of type I,II,III appliances	High sampling rate and repeatable transient profile
Start-Up Current Transients [6,20,23]	Current spikes and shape of switching transients	Detects Type I and Type II appliances	Appliance specific and fails for type III and type IV appliances

IV. SURVEY OF NILM TECHNIQUES BASED ON APPLIANCE RECOGNITION ALGORITHM

Researchers have employed many practices for energy disaggregation. Early authors proposed supervised approaches which had a disadvantage of labeling and training overhead. Then unsupervised approaches came forth which still suffered training expense because it unlabeled data for training. Recently, researchers have overcome this overhead by employing training less approach.

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NILM Based on Supervised Approaches

Supervised approaches in NILM are broadly classified as optimization and pattern matching based method.

Optimization based Supervised Methods

Optimization based methods compares the captured feature an unknown appliance to the present pool of the load database. Researchers [28, 3] proposed different optimization techniques using genetic algorithms and integer programming. But there exists a challenge due to its increased complexity of comparison in the presence of unknown appliances and appliances with overlapping power feature.

Pattern Matching Based Supervised Methods

Pattern matching is the most simple and most frequently employed approach for energy disaggregation. Pattern matching algorithm could be traces in early works of Hart [5] in which loads form their distinct clusters in the active and reactive power plane. For load identification, the steady-state events are mapped to an appliance feature space. And then, clustering analysis is performed to verify if the new feature already exists along known clusters. Though this method appears it cannot identify appliances with overlapping power and real time features.

Researchers [7, 30- 32] have tried to improve the disaggregation performance through smoothing and filtering aggregated power before recognition of appliances, but is highly complex due to excessive training. Another author [1] made use of the Bayesian method where power was used to identify the likely state of an appliance. Bayesian classifier is assigned to each individual appliance and trained accordingly.

However this approach fails for appliances whose operation are correlated. Authors have used temporal information along with real power values for performing load disaggregation [2, 33]. Researchers have also used techniques namely Hidden Markov Models (HMM) Artificial Neural Networks (ANN) [34] for load disaggregation. Construction of HMM models for large number of appliances is quite exhaustive and complex. For each new appliance added HMM models have to be retrained which is also a challenge

Alternatively, ANN [11] works well for large number of appliances. However it needs exhaustive training for each load. On the other hand, Support Vector Machines (SVM) using low frequency features and harmonic signatures has shown good performance in disaggregating appliances [17, 36, and 33]. Liang et al. [3, 37] have used committee decision mechanisms (CDM) to perform disaggregation aimed to increase its accuracy.

NILM based on Unsupervised Approaches

Since supervised NILM approaches require prior information for training researchers looked for approaches that doesn't require such information. Therefore, researchers utilized unsupervised learning NILM which offered wider applicability. In [38], a blind disaggregation technique has been applied to classify appliances in an unsupervised manner. Real and reactive powers were used as appliance features.

And many unsupervised practices such as agglomerative clustering and Genetic K-means approaches were used for disaggregation. The matching pursuit (MP) algorithm iteratively reduces the distance between a new unknown event and all the clusters as shown in Figure 4. This approach works for high power residential appliances but fails for low powered appliances.

Another unsupervised energy disaggregation approach used was [39] motif mining which identifies recurring events which are usually the ON/OFF operation of the appliance. This approach is possible only for loads that have distinct and repeatable events but it is not clear as to how this technique will work with appliances with non-repeatable consumption pattern as well loads with similar consumption pattern.

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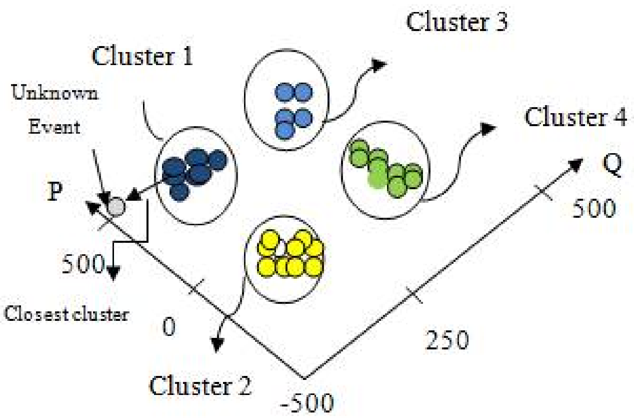

Figure 4. Matching Pursuit Algorithm

Kim et al. [40] built probabilistic models of load behavior using variants of Factorial HMM (FHMM). To model appliance specific HMMs non-power features like time and duration of load usage and real power consumption patterns were used.

The aggregated appliance data (Y) at time t depends on the power consumed by the devices functioning in their specific states. On the other hand FHMM is more suited to model the communication between devices. Hence, given Ythe goal is to find the exact possible hidden state sequence (q) which might have caused the observation. Parameters of this model were learned using Expectation Maximization (EM) algorithm and to find the best possible q* Gibbs sampling was used as shown in Eq. (2),

$$q^* = \text{argmax } q \; P(Y,q|\lambda) \qquad (2)$$

Of all the FHMM models, Conditional Factorial Hidden Semi-Markov Model (CFHSMM) showed the best disaggregation performance with 83% accuracy. However, the performance reduces as the number of appliances increases. And also it does not consider multistate appliances and there is no discussion about model for unknown appliances.

In order to overcome this issue, [41] new algorithm called Additive Factorial Approximate MAP (AFMAP) was developed. Compared to the previous inference methods this approach performs well. AFMAP could disaggregate loads with a precision of 87% but the precision falls for electronics and kitchen outlets to less than 50%.

Another approach Hierarchical Dirichlet Process Hidden Semi Markov Model (HDP-HSMM) [42] an unsupervised approach was used for power disaggregation. The HDP-HSMM has the ability to disaggregate multistate appliances as opposed to previous inference approaches [40, 43].

4.3 NILM Based on Graph Signal Processing

Recently developed approach where the power events are represented in the form of graph. The emerging graph signal processing has solution for various problems wherein data are converted to graphical forms. The first GSP based approach is supervised and only for classification GSP was used.

Compared to machine-learning approaches, like Hidden Markov Model (HMM), which requires lot of observations in order to construct a graph, graph signal processing approach takes an different approach in building a graph without knowing signal’s statistics [11].Recent GSP based NILM energy disaggregation uses GSP three times for event detection, clustering, and for feature matching. This approach disaggregates without any training.

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TABLE 3.

Comparing Appliance Recognition Algorithms

Algorithm	Accuracy	Training	Load Detected
SVM [37,11,36]	75–98	Supervised	I,II,III,IV
HMM [40,41,42]	75–95	Supervised	I & II
Bayes [1,43,33]	80–99	Supervised	I & II
KNN [5,44,45]	60-97	Supervised	I & II
Neural Networks [6,17,46]	80-97	Supervised	I & II & III
Graph signal Processing [43]	77-80	___________	I & II

V. SURVEY OF NILM TECHNIQUES BASED ON THE LOAD MONITORING MEASUREMENTS

There are various measurements and electrical characteristics considered for load monitoring. Primitive measurements are current and voltage. There are measurements which are derived from primitive measurements: real power, reactive power, power factor, and energy.

And also, there exists advanced measurements like electromagnetic interference (EMI) and harmonic distortion. Electrical characteristics, such as startup, aggregate values (minimum, maximum, average) and shutdown signatures. And even more advanced measurements such as eigen values requires high frequency meters to be monitored.

Measurements such as EMI, harmonics and transient waves need expensive equipment, and thus fail to be practiced. The summation of these measurements is also not possible since data is acquired from smart meter. The cost required for the equipment would be greater than the energyconserved. Hence such approaches bring down the purpose of energy conservation.

TABLE 4.

Measurements Considered for Load Monitoring

Measurements	Main Feature	Inference
Voltage and current [21]	Improved recognition accuracy and computation speed	Combined transient and Steady state signatures
Power, reactive power [5]	Constructed P,Q plot to disaggregate appliances	Not suitable for small appliances

Power, reactive power and transient waves [6]	Additionally used transient waves to detect non steady state operation of an appliance	Costs more computational power
Power, reactive power and harmonics [23]	Detects overlapped loads in P,Q plots	Their analysis leads to a form of equipment diagnostics, linking transients to equipment specific mechanical and electrical faults.
EMI [14]	Detects simultaneous appliance events.	Requires specialized equipment with constant training for each appliance
Voltage, current and power factor [12]	Used steady state signatures	Exponential computational when more number of appliances are added

VI. CONCLUSION

NILM has gained considerable amount of momentum in the smart-energy domain and this work presents a survey of algorithms used for energy disaggregation. In this paper, the three key areas that differentiate an NILM approach are focused namely

- Appliance feature used
- Appliance recognition algorithm used
- Load Monitoring strategy practiced

From the survey conducted the following conclusions are drawn

1. **Appliance feature:** Steady state features such as power, active power are less complex and could be easily captured from a low sampling rate energy meters but fails to disaggregate low powered devices. On the other hand transient features require expensive high sampling rate meters but can disaggregate low powered devices.

2. **Appliance Recognition algorithm:** In the past many machine learning algorithms were proposed but they had a training overhead. But the most recent graph signal processing approach functions without training.

3. **Load Monitoring Strategy:** Primitive measurements such as active power, power factor are less expensive while advanced measurements such as eigen values and harmonics requires costly devices to monitor the load.

Future techniques in NILM should focus more on training-less and a low cost solution and energy disaggregation should detect multistate appliances and simultaneous operation of an appliance as well.

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