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A Low Rate Energy Disaggregation using Non-Intrusive Load Monitoring

M.P. Rajakumar, J. Ramya, C. Shanmuga Priya

Abstract: ***Nowadays, Energy conservation and management are a must practice due to the exponentially increasing energy usage. One solution for providing for energy conservation is appliance load monitoring. Load monitoring approach should be simple and of low cost in order to be massively deployable. Non-Intrusive load monitoring is a better approach since it can disaggregate energy at the cost of single energy meter. A low sampling rate energy meter incurs low cost compared to a high sampling rate energy meter. In this paper a less complex, low cost energy disaggregation approach has been proposed.***

Keywords: Appliance Load Monitoring (ALM), Energy Disaggregation, Intrusive Load Monitoring (ILM), Non-Intrusive Load Monitoring (NILM).

I. INTRODUCTION

Electricity is one of the irresistible commodities that are used every day. The awareness of power consumed by independent appliances rather than only knowing aggregated power shown by an electric meter can help the consumers conveniently know how the energy has been consumed with an insight of energy conservation. The method of splitting the singular devices power from the accumulated load is termed as capacity disaggregation. It is likely to attach an intermediate observing device between the power point and the piece of equipment and then record its actions. This methodology is normally known as "intrusive" nursing. This mode is costly and ill-timed for extensive deployment. The other attractive method known as NILM, which can regulate the functioning plan of electrical consignments in an objective system from quantities made at a central situation. For a commoner to utilize the advantage of energy disaggregation one has to employ a low rate and less complex non-intrusive load monitoring approach. Hence, active power is a measurement that should be considered while load monitoring since it could be obtained from a low cost as well as a low sampling rate energy meter. Traditional approaches have employed either supervised or unsupervised machine learning algorithms for energy disaggregation. Researchers have used employed different classes of measurements for feature extraction such as voltage, power factor, current harmonics and active power. Though current harmonics and even some advanced measurements such as Eigen values, transient traits provide us with good disaggregation they are still they are ineffective since they demand high sampling rate energy meter or some other specialized high cost tool for measuring. This paper proposes a low rate as well as a less complex approach where the customer is completely freed from the entire process of energy disaggregation.

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***Correspondence Author(s)**
M.P. Rajakumar, Associate Professor, St. Joseph's College of Engineering, Chennai, Tamilnadu. rajranjhu@gmail.com
J. Ramya, Associate Professor, St. Joseph's College of Engineering, Chennai, Tamilnadu. ramharsha@gmail.com
C. Shanmuga Priya, Assistant Professor, St. Joseph's Institute of Technology, Chennai, Tamilnadu. priyashanmu415@gmail.com

II. RELATED WORKS

Since 1980s large number of research efforts have focused on non-intrusive load monitoring [1]-[3]. According to [4], researchers have still not found the best solution that works well for all kinds of loads or appliance types. To date, no sole result stands out to crack all the complications in NILM. Non-intrusive load monitoring is usually performed using signatures which are of two kinds of steady and transient signatures of appliances to be monitored. These signatures are obtained from a prior labelled training data and hence used to recognize the appliances from total load data [5].

Researchers have also developed event detectors are developed to identify the various behavioral patterns of appliances through classification strategies [6], [7], [8]. Spectral domain features were also used for energy disaggregation, yet such features required complex machine learning methods and sophisticated monitoring devices [9]. Hidden Markov model (HMM) is a widely practiced approach for energy disaggregation, wherein the appliances' change of state are acquired and trained to a appliance model and then hidden states of each load are inferred through observed probabilities for each appliance states [10].

Many variants were also tried by researchers over HMM which are Factorial HMM (FHMM), Conditional Factorial Hidden Semi-Markov Model (CFHSMM) [11] and Additive Factorial Approximate MAP (AFMAP) [12]. However, these techniques require a more number of trainings and are usually complex. Hence researchers looked for an alternate solution which gave away to unsupervised approach which had wider applicability. In [13], training less disaggregation technique has been adopted to disaggregate appliances in an unsupervised way. Some other unsupervised practices applied were agglomerative clustering and Genetic K-means approaches.

Matching pursuit algorithm approach performs well for high power residential loads but its performance degrades for low powered appliances. Motif mining [14] another unsupervised approach which recognizes recurring events to disaggregate loads. This approach functions only for loads that have unique and repeatable events. Hence training less and a low cost disaggregation approach are required for a wide applicability of NILM.

III. NON-INTRUSIVE LOAD MONITORING

One of the most innovative ways of conserving energy is monitoring the power usage day to day. In order to bring about this, as in [1], researchers have brought the concept of Appliance Load Monitoring (ALM) which could sense energy as well as disaggregate energy. ALM is of two types namely ILM and NILM. NILM captures the appliance precise signatures commencing the accumulated load data which is measured through an energy meter connected outside the residence whereas ILM stands for distributed sensing wherein meters are connected inside the residence. Intrusive-load monitoring requires modification of the entire electrical circuit of a residence. The framework of the recommended NILM approach is given below in Fig. 1.

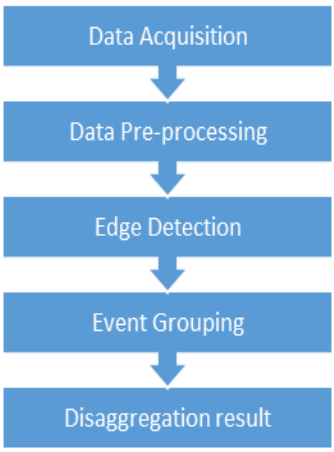

Fig. 1. Framework of proposed NILM approach

Description of each of the modules is provided in the next section. The task is to disaggregate the entire house or a building's aggregated energy into its constituents. Requirements to perform non-intrusive load monitoring is an energy meter which measures aggregated load of a residence for extracting steady state features (power, active power, power factor etc.) or sophisticated devices for measuring transient features (appliance specific).

This energy meter could be either low sampling or high sampling rate meter. Sampling level plays an essential part in mining of structures. For capturing complex order harmonics of signals, sampling rate should satisfy Nyquist–Shannon sampling benchmarks. Low sampling rate energy meter is sufficient for capturing steady state features such as active power, reactive power etc.

IV. PROBLEM DEFINITION

NILM is an approach for disaggregating electrical appliances from aggregated power data by looking for load specific energy consumption patterns. The aggregated power data is acquired from an energy meter .The problem of energy disaggregation can well be explained as follows: the accumulated power is denoted as P(t) and is arithmetically characterized in (1)

$$\Pi(\tau) = \pi 1(\tau) + \pi 2(\tau) + \ldots + \pi \nu(\tau) \qquad (1)$$

The aggregated power is denoted as P(t) and is mathematically represented in (1) where n is the unknown number of appliances within the time period t and p_i is the power consumed by each individual load.

The task is to disaggregate the aggregated power P(t) into individual load power signals.

V. PROPOSED SYSTEM

In this section, the proposed approach of disaggregating aggregated power into individual appliance signals at a truncated sampling rate is described. The suggested approach has modules namely data acquisition, data pre-processing, feature extraction and disaggregation result and its architecture is given below in Fig. 2. Each of the modules is elaborated below:

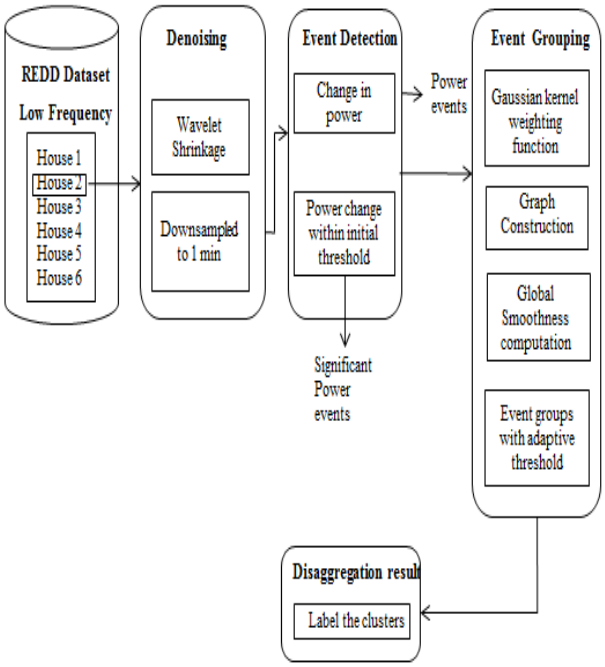

Fig. 2. Architecture of proposed system

A. Data Acquisition

In order to perform energy disaggregation, aggregated power monitored by a low sampling energy meter is required. This power data is obtained from freely accessible dataset which is shown in Fig. 3. REDD provides two kinds of aggregated power data, one is measured by a high sampling rate energy meter and another is calculated by a truncated sampling rate energy meter. Low sampling frequency data is picked for performing proposed energy disaggregation. REDD provides base load as well as disaggregated appliances load.

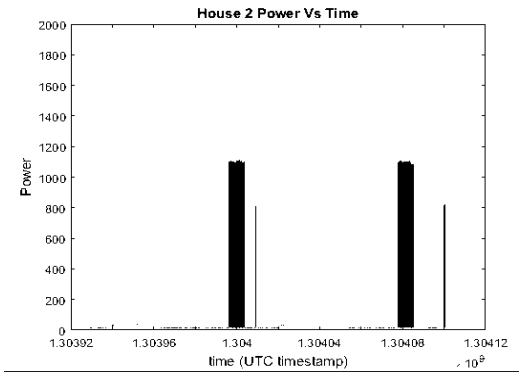

Fig. 3. Power Vs time

B. Data Pre-processing

The aggregated power data obtained is noise prone and hence has to be filtered for effective energy disaggregation. Wavelet Decomposition is a widely practiced method for noise removal in several field of signal processing (e.g. EOG , ECG signal denoising) . So as to complete signal denoising, wavelet shrinkage method is employed. First, the unique signal is converted into the wavelet realm followed by decomposition. After this, a selected brink value is applied to the wavelet coefficients. The denoised signal obtained is down sampled to one minute. The resultant denoised signal is shown in Fig. 4.

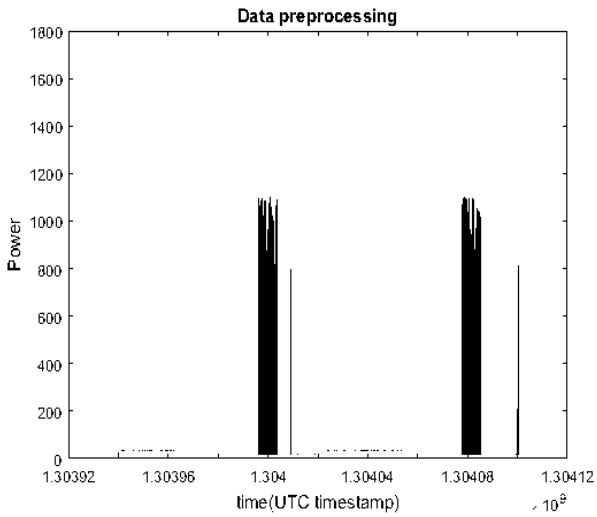

Fig. 4. Denoising through wavelet decomposition

Table – I: Appliance Features

Features	Description
ΔP	The change in power
S*	Global smoothness of the graph generated
ρ	Standard deviation of Gaussian kernel weighting function
A	Augmented Matrix with power events as vertices

C. Edge Detection

Power monitored for an entire residence is constantly altering (rising and falling, steps). These changes (should be significant enough) can indicate that an event has occurred. This event is referred as edge detection. Power event is described is the power variation across the aggregated power data. It can be formulated as in (2).

$$\Delta P_t = P_{t+1} - P_t \qquad (2)$$

Where ΔP_t is the event that occurred at time instant t. It is necessary to include significant events for edge detection. Since power variation might be caused even due to electric noise or transient appliance-specific noise. Hence, initially a small threshold of 10 W is chosen and power variation of 10 W and more than 10 W are considered as significant events. These significant events alone are considered for energy disaggregation. Significant power events can be formulated as below in (3).

$$\Delta P_t \in (-\infty, -10) \cup (10, \infty) \qquad (3)$$

Significant power events so obtained are either positive event or negative event which is shown in Fig. 5.

Algorithm 1 Edge Detection

Input: aggregated power (P)

Output: significant power events (ΔP)

```
for i=1:size (P)
    ΔP_t = ΔP_t+1 - ΔP_t ;
end
for i=1:size (P)
    if (ΔP_t >=10 || ΔP_t <= -10)
            ΔP_t = ΔP_t ;
    else
            ΔPi = 0;
    end
end
```

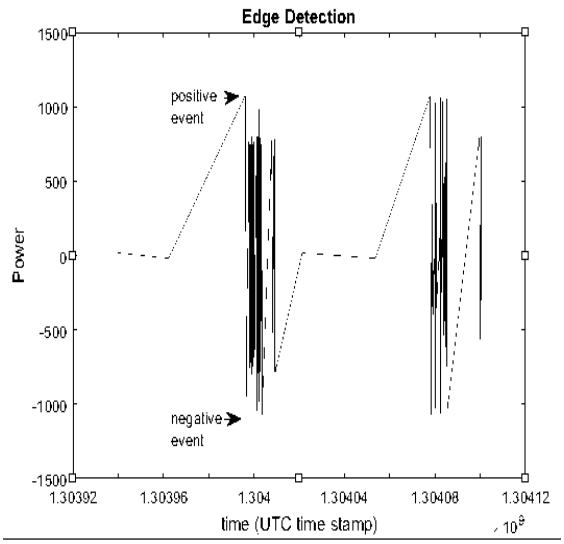

Fig. 5. Edge Detection

D. Event Grouping

The next stage is to group statistically similar events together. In order to perform an adaptive threshold is derived through global smoothness computation. With the acquired set of power measurements p, a graph G = {V,A} is defined, where each vertex vi ∈ V matches to each attained power measurement and the edges amongst the vertex is given by a adjacency matrix A. The adjacency matrix A shows the edges between the nodes in their graph G in the graph and their corresponding weights. Adjacency matrix is defined by a Gaussian kernel weighting function. It is mathematically represented as in (4).

$$W_{ij} = \exp\left\{-\frac{|dist(Pi,Pj)|^2}{\rho^2}\right\} \qquad (4)$$

The distance between the edges is taken as Euclidean distance and ρ is the scaling factor. The graph signal denoted by s, maps between nodes V to a set of composite numbers, where each individual element s_i is mapped to a node $v_i \in V$.

A graph signal's global smoothness of the underlying graph can be expressed mathematically as in (5).

$$\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}\,(s_i - s_j)^2 \quad (5)$$

The global smoothness optimization solution s^* is mathematically formulated as in [z] in (6).

$$s^* = L^{\#}_{2:N;2:N}\,(-s_1)L^{T}_{1,2:N} \quad (6)$$

where **L** is the Laplacian operator defined in (7).

$$L = D - W \quad (7)$$

where D is a diagonal matrix defined by $D_{i,i} = \sum_j W_{i,j}$.

Algorithm 2 Event Grouping

Input: significant power events (ΔP)

Output: grouped events (GE)

```
for i=1: size (ΔP)
    for j=1: size (ΔP)
        Compute augmented matrix W;
    end
end
for each event ΔP
    Compute diagonal Matrix D;
end
for each event ΔP
    Compute Laplacian using D and W;
end
for each event ΔP
    Assign '1' for positive and '-1' for negative event
end
for each event ΔP
    Compute global smoothness's'
end
for each event ΔP
    GE = Use's' as adaptive threshold and group events
end
return GE;
```

E. Disaggregation Result

In the previous section, events are grouped to equal number of positive and negative clusters. Once the events have been segregated in this manner, energy disaggregation has taken place. Each element in the group is the power consumed by an appliance. Each disaggregated event is given a label through the process of pattern matching. It is done by associating the disaggregated event with an already present database of load signatures which can at first be done via short-time diary [15] or a crowd-sourcing, i.e., the pattern is extracted when the resident switches on and off their devices in their residence. If there is no label in the database, the devices would be entered in the database and it is arbitrary labelled. The end result of disaggregation is shown below in Table II.

Table – II: Energy Disaggregation Result of House 2

Appliance Name	Disaggregation result (in KW)	Ground truth result (in KW)
Kitchen_outlet1	803	805
Disposal	624	609
Washer dryer	56	55
Stove	402	457
Kitchen_outlet2	1077	1119

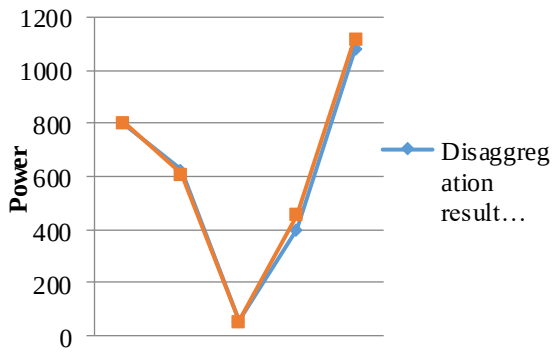

Fig. 6. Energy disaggregation result of House 2

VI. RESULTS AND DISCUSSION

It is observed that the recommended disaggregation technique function well only if the power consumed by each appliance is unique enough from other loads in the residence and power consumed by each appliance does not fluctuate often.. As input, accumulated active power readings of House2 from REDD dataset [16] is taken denoised and down sampled to 1 minute. The REDD dataset is widely used for the practice of different NILM approaches [17], [18], [19], [20], [21], [22]. REDD houses contains aggregated power readings of various appliances along with the presence of small number of unknown appliances too. House 2 readings are taken for performing disaggregation it includes appliances such as kitchen outlets, lighting, stove, microwave, washer and disposal. Three different types of cases are considered for analysis.

A. Case study I - House 3

REDD dataset House 3 power readings consists of twenty varied appliances.

The proposed energy disaggregation algorithm is applied over House 3 and energy disaggregation results of few appliances are listed below in Table III.

It is observed that there is only slight variation of the disaggregation result from ground truth result

Table – III: Energy Disaggregation Result of House 3

Appliance Name	Disaggregation result (in KW)	Ground truth result (in KW)
Electronics	1333	1321
Disposal	512	571
Dishwasher	2228	2246
Outlet_unknown	940	973
Outlet_unknown	20	18

B. Case study II - House 1

REDD House 2 comprises the lowest number of power states among the three houses namely house 1, 2 and 6. Additionally, House 2 also has a low load and time complexity which also concludes that House 2 is comparatively the simplest house to disaggregate. Similarly, House 1 has the same number of loads as House 2, but the number of power states is more, and eventually is more difficult to disaggregate. The proposed algorithm is applied to House 1 and disaggregation result is represented Table IV.

Table – IV: Energy Disaggregation Result of House 1

Appliance Name	Disaggregation result (in KW)	Ground truth result (in KW)
Oven	1710	1725
Refrigerator	2492	2359
Dishwasher	1538	1566
Oven	2551	2590
Kitchen_outlet	125	128

C. Case study III - House 4

The proposed system results are also obtained for house 4 of REDD dataset. House 4 consists of 18 different loads. Some of the appliances in House 4 are smoke alarms, air conditioning and furnace. The proposed algorithm is applied to House 1 and disaggregation result is represented Table V.

Table – V: Energy Disaggregation Result of House 5

Appliance Name	Disaggregation result (in KW)	Ground truth result (in KW)
Miscellaneous	47	44
Air_conditioning	124	130
Lighting	189	181
Air_conditioning	124	130
Outlet_unknown	88	84

VII. CONCLUSION

In this paper, a novel, low rate, unsupervised NILM approach is developed. The key inspiration comes from the point that high sampling rate energy though effective for disaggregation are quite expensive and hence low sampling rate energy meter is opted which too could accurately capture signal patterns with low implementation complexity. REDD dataset have been utilized for this NILM technique where disaggregation is done without the need for any online or offline training. The proposed system makes use of low sampling rate aggregate data to perform energy disaggregation.

Because of its modest set-up and smallest amount of end-user input (for prior labelling) this algorithm can be massively deployable for providing customer services. This paper has made use of Graph signal processing for load disaggregation and cases were considered for better perspective. Future work will focus on more robust algorithm for performing disaggregation over multi-state appliances and also detect simultaneous operation of appliances.

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AUTHORS PROFILE

Dr.M.P.Rajakumar received M.E (Computer Science) Degree from Sathyabama University, Chennai, India and Ph.D. Degree (Faculty of Computer Science and Engineering) from Sathyabama University. He is currently working as a Associate Professor in the Department of Computer Science and Engineering at St. Joseph's College of Engineering, Chennai-600119, India. His research interests include Computational Intelligent techniques, Theoretical Computer Science and Machine Learning Techniques.

Dr.J.Ramya received M.E (Computer Science) Degree from Anna University, Chennai, India and Ph.D Degree (Faculty of Computer Science and Engineering) from Jawaharlal Nehru Technological University, Hyderabad. She is currently working as a Associate Professor in the Department of Computer Science and Engineering at St.Joseph's College of Engineering, Chennai-600119, India. Her research interests include Image Processing and Machine Learning Techniques.

Ms.C.Shanmu Priya received M.E (Computer Science) Degree from Anna University, Chennai, India. She is currently working as a Assistant Professor in the Department of Information Technology at St. Joseph's Institute of Technology, Chennai-600119, India. She published papers in the field of Energy Management. Her research interests include Image Processing, Effective Energy Management Scheme and Machine Learning Techniques.