NON-INTRUSIVE LOAD DISAGGREGATION METHODS FOR LOW-RATE SMART METER DATA

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ABSTRACT

Smart meter technology presents an opportunity to gain better insights into consumer appliance usage and consumption behaviour. Load monitoring can provide valuable data on appliance specific energy consumption statistics which in turn will be useful for the consumer to evolve an optimum energy utilization strategy. In the utility point of view, the data acquired in this manner could be used to evolve better target demand side management programs, including demand response and energy efficiency. Non-intrusive load monitoring (NILM) is a consumer energy disaggregation technique that segregates individual appliance energy consumption from the total energy measured at the mains. Unlike intrusive load monitoring, it does not require separate meters to measure individual device consumption. This field has garnered lot of research interest recently, owing to emergence of smart grid technologies and advances in smart metering. Machine learning algorithms are predominantly used to solve NILM problems. In view of concerns regarding customer privacy and economics, low frequency smart meters are preferred. There are many challenges involved in using low granularity data for NILM algorithms. This work summarizes the current state of the art of NILM methods for low rate smart meter data. The limitations of the present methods and scope for future work are also presented.

Keywords— Energy disaggregation, Non-Intrusive Load Monitoring (NILM), Smart meters, Data granularity

INTRODUCTION

In India, residential sector represents around 24% of the total energy demand. According to Energy Efficiency Services Limited (EESL), 25 crore conventional electricity meters will be eventually replaced with smart meters across our country [1]. Smart energy meter is an electronic device which records aggregated consumer electricity consumption and reports in short intervals of time. It is deployed at the utility service entry. It enables two-way communication between meter and the electricity distributer.

Electrical energy consumption pattern of a consumer can be meticulously investigated by duly monitoring all individual appliances operations. Non-intrusive load monitoring (NILM) is the process of disaggregating the total electricity consumption measured at the mains into constituent appliance consumptions with the help of electrical data acquisition system and signal processing algorithms. The aggregate data is received from the main electric panel using smart meters. It is non-intrusive since the method does not require any meter installation at device levels. Research on NILM started during 1980s in Massachusetts Institute of Technology (MIT) by George W. Hart [2]. This idea got a fresh impetus recently due to the vast advancements that happened in the fields of smart meters, improved computational power and advances in machine learning and statistical techniques.

Non-intrusive load monitoring has many potential applications from both energy companies as well as their customers. Customers will have a detailed bill information without investing for individual meters for their appliances. This will help the customer to plan for energy savings and reductions in electricity bills. NILM results can be used to identify malfunctioning of customer appliances. It can be also used for occupancy detection. While planning for demand response, distribution companies can identify potential customers with the help of their disaggregated load data. They may also identify critical loads like electric vehicle charging, so as to plan for upgradation of elements like distribution transformers [3].

All NILM approaches follow three steps namely data acquisition, feature extraction and load classification and energy disaggregation. Data acquisition unit measures the aggregated energy consumption and with the help of signal processing techniques data is pre-processed and cleaned. There are two categories of smart energy meters available to do the job- high frequency meters and low frequency meters. High frequency energy meters measures aggregated energy at sampling rates from 1Hz to kHz ranges. They are expensive due to complex hardware and are custom-made to extract extra features from the signal [4].

PROBLEM STATEMENT

Problem statement of NILM is given in (1):

$$\hat{x}(t) = \sum_{i=1}^{n} x_i(t) + e(t) \qquad (1)$$

where $\hat{x}(t)$ is the aggregate electrical signal, n is the total number of appliances, $x_i(t)$ is the individual appliance contribution and $e(t)$ is the noise that includes measurement errors and all unknown appliances. In most of the cases, the electric signal will be active power. NILM can be classified as a single-channel Blind Source Separation (BSS) problem. In this case, aggregate power consumption signals flow through the electric line from the multiple devices to the smart meter [5].

NILM Framework

Every electrical appliance demonstrates a distinctive energy pattern termed as appliance signature. Based on the operational states, electrical appliances can be classified into five types. Type-1 appliances have two states of operation namely ON and OFF. Lamp, toasters are typical examples of this category. The second category consists of Finite State Machines having finite number of operating states. Washing machine is a multi-state FSM device. Type-III devices do not have fixed number of states and draw variable power during their operation. They are also known as Continuously Variable Devices. Power drill is an example of continuously variable devices. Permanent consumer devices are called Type-IV devices since they are active permanently. Refrigerators and telephone sets are example for permanent consumer devices [6].

According to the literature survey, NILM process consists of three stages as shown in figure.1. They are electrical signal acquisition, appliance feature extraction and appliance classification.

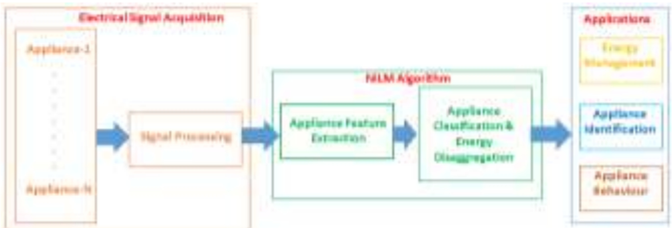


Fig.1. NILM framework

Data Acquisition

This module acquire the aggregated energy consumption pattern at fixed intervals of time. This is usually done by smart meters. They are classified into high sampling rate meters and low sampling rate meters. Data collected by high sampling rate meters have frequency greater than 1Hz. Most of the smart meters deployed now-a-days are of low sampling rate type. They have sampling rate lower than 1Hz and in many cases data is collected once in several minutes or even hours [3].

There are many public energy disaggregation datasets available in literature. They are collections of realistic energy measurements taken from real-world scenarios. Some of the popular datasets are REDDIT, REFIT, BLUED, UK-DALE and BLUED [7].

Feature Extraction

In this step, event detection module extracts various events by analysing changes in power levels. Features are derived with the help of these events. The features can be steady-state, transient-state or non-traditional features. Steady-state features such as variations in real power and reactive power that are obtained from the steady state operation of the appliance. Transient-state features are extracted from the transient state operation of the device. They can be current spikes, transient response time etc. Characteristics like time of operation of a device, correlation of usage of different devices are examples of non-traditional features [3].

APPLIANCE CLASSIFICATION AND ENERGY DISAGGREGATION

Once the required features are extracted from the raw energy data, appliance specific states are identified using load identification algorithms. Appliance classification methods can be either supervised methods or non-supervised methods [8].

i. Supervised disaggregation methods

They require pre-labelled data for training the classifier. They are classified into optimization approaches (simultaneous matching) and pattern recognition (one to one matching) approaches [8].

In case of optimization based approaches, extracted features are compared with the appliance features stored in the data base. Integer programming and genetic algorithm are reported in some of the NILM literatures [9], [10], [11], [12].

Pattern recognition approaches detect the most probable state of the suitable device states. Most of the work on NILM are based on pattern recognition methods. The pioneering work in NILM led by Hart was based on pattern recognition method [6]. Various device-specific features of different devices are stored in a database. Devices form specific clusters in P-Q plane. Steady-state changes of P and Q are mapped to the feature space. Clustering analysis is conducted to identify different appliances. In 2012, Weiss et al. added distortion power as a feature [13]. Bayes classifiers were used by Marchiori et al. Artificial Neural Network (ANN) based NILM and Hidden Markov Models (HMM) are also being used in pattern recognition based NILM [14], [15], [16]. In case of low-rate data Support Vector Machine (SVM) performs well for disaggregating loads [17], [18].

ii. Unsupervised disaggregation methods

They do not have pre-training procedures. In this method, the prior data which are trained before testing part, in case of supervised methods are extracted from the test data itself. They are non-event-based methods and tries to disaggregate the appliance consumption directly [19]. Blind Source Separation technique, Motif Mining approach and variants of Factorial Hidden Markov Models FHMM) have been used in unsupervised approach of energy disaggregation problems [20], [21]. [22], [23].

Challenges

NILM is a contemporary and evolving area of research. Some of the challenges faced in this area are the following:

1. Sample rate of raw data: The accuracy of NILM algorithm increases with the input sample rate. Residential smart meters usually saves data at 15min to 1h time intervals. NILM algorithms are developed for specific sample rates. Sample rates above 1Hz are known as high frequency samples and those below 1Hz are called low frequency samples. Electrical signature extraction is difficult in case of low rate samples.

2. Compilation of representative electrical characteristics: For feature extraction and classification, researchers have used many electrical parameters like energy, active and reactive powers, current and voltages,

power factor, harmonic distortions, electromagnetic interference etc. Generic smart meters usually measures active powers alone. Advanced electrical characteristics requires expensive measurements at very high frequencies.

3. Discriminating similar characteristic devices: Practically it is difficult to differentiate devices having similar power levels. Instances where multiple operations of ON and OFF of devices and simultaneous operation of similar devices leads to incorrect models.

4. Different types of appliances: Different houses have machines of different makes. Also devices varies in their modes of operations. Classification of appliances in this scenario is a difficult task.

5. Noise: There can be noise in the measured electrical signals due to harmonics, voltage fluctuations in appliance consumptions, noise due to change of state of operation etc.

6. Dynamic and changing consumption pattern: Consumer behaviour is dynamic. For example household consumption on weekdays and weekends are different. Also appliance may be replaced in long term.

7. Computational cost: NILM algorithms have to process online data and generate the results in real-time. This will be computationally expensive.

8. Availability of city-specific datasets: There are a lot of public electrical disaggregation datasets available. However data specific to only a few cities are available in open domain.

NON-INTRUSIVE LOAD DISAGGREGATION METHODS FOR LOW-RATE SMART METER DATA

Low frequency energy meters measures aggregate energy at a granularity of 1s and above. Popularly used smart meters are of this category due to government regulations on privacy issues. Also they are economical. Implementing NILM using low rate input data have many challenges.

1. During data acquisition process, type of information that can be extracted from a signal depends on its sampling rate. Using low rate meters, only tradition power metrics like active and reactive powers can be measured.

2. In case of low frequency data, during feature extraction process transient features like shape, harmonics etc. cannot be extracted. Steady state signatures only can be extracted in this case.

3. Identifying low power appliances with overlapping steady-state features or those turned on at nearly same time are difficult in case of low rate aggregated energy input.

In the following sections literature survey on NILM solutions to low granular aggregated energy input data is presented.

Non-intrusive load disaggregation solutions for very low-rate smart meter data using optimization, graph signal processing and convolution neural network algorithms [24]

In 2020 Zhao et al. proposed three load disaggregation algorithms based on optimization, graph signal processing and convolutional neural networks. They focused on hourly electricity data for a period longer than one year [24].

The proposed optimization based (OPT) approach did not have training of model. The inputs taken were aggregated load data, and appliance details. The entire method was divided into two steps. In the first step, always–on devices were estimated and removed. In the second step the consumption of remaining devices were estimated.

Aggregate load is given as (2):

$E_i = \sum_{m \in M} E_i^m + \sum_{m \in N} E_i^m + n_i$ (2)

where M is the total number of devices that are always-on, N is the set of other devices, n_i is the noise due to measurement error and unknown devices. Separating the always-on devices as (3)

$\hat{E} = E_i - \sum_{m \in M} E_i^m$ (3)

Then the optimization problem can be written as (4)

$arg\ .min \sum_{i=1}^{N} \left| \hat{E} - \sum_{m \in N} E_i^m \right|$ (4)

where N is the total number of samples to be disaggregated.

In the proposed algorithm initially always-on loads were estimated focussing on 12 AM to 5 AM consumption. In the subsequent steps, always-on loads were not deducted from the dataset. In the next step, appliances were modelled under two categories based on the appliance ratings. The first load category like washing machines had pre-set modes of operations or consumed almost constant energy during usage. Loads having constant rated power; but variable duration of use like computers were considered in the second category. In the last step of the algorithm not-always-on devices were disaggregated by solving the optimization problem given in (2.3). The algorithm is shown in figure 2.

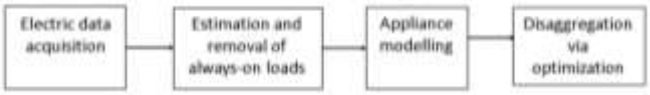


Fig.2. Schematic for OPT algorithm [24]

The authors of [24] proposed a second disaggregation algorithm based on unsupervised Graph signal processing where clustering was conducted by generating two graphs. Once all samples were clustered and labelled, disaggregated load profiles were evaluated using relative standard deviation, RSD.

In the third approach proposed by the authors of [24] Convolution Neural Network (CNN) was used. Hourly aggregate power consumption and encoded cyclical continuous absolute time features were used as inputs. Window length was set to 7h and three CNN blocks were used.

Optimization based algorithm and Graph Signal Processing based algorithms were implemented in MATLAB 2016a and Convolution Neural Network approach was implemented in Python. Public load disaggregation dataset REFIT was used as raw data for all the three algorithms. The implemented algorithms were benchmarked against Factorial Hidden Markov Model, combinatorial optimization and discriminative disaggregation sparse coding methods.

It was concluded that CNN based algorithm and optimization-based algorithm exhibited better disaggregation performance. CNN based method was faster compared with OTP. Since CNN is a supervised method, it requires prior training using sub-metered data which is not required for OTP based and GSP based unsupervised methods.

Data mining of smart meters for load category based disaggregation of residential power consumption using genetic algorithm [25]

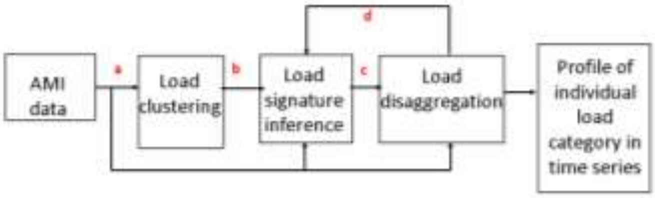
Zhang et al. proposed an unsupervised load-category-based disaggregation method that used hourly smart meter data [25]. With the help of clustering and optimization methods, load signatures were extracted using active and reactive powers. Appliance details were not taken as input in this method. From the aggregated active and reactive powers obtained from smart meters, signatures of possible load categories were extracted. Using Weighted Least Squares method, individual load categories based on similar average power factors were separated. Final disaggregation of active and reactive powers for load categories were implemented using optimization approach based on Genetic algorithm.

Disaggregation of active and reactive powers are expressed as (5) and (6).

$$P^{(t)} = \sum_{i=1}^{N} x_i^{(t)} + \epsilon_P \; for \; x_i^{(t)} \in \left[x_i^{min}, x_i^{max}\right] \quad (5)$$

$$Q^{(t)} = \sum_{i=1}^{N} x_i^{(t)} \tan(\theta_i) + \epsilon_Q \quad (6)$$

where x_i^((t)) is the real power of the ith appliance at time t, θ_i is the power angle, N is the total number of load categories, ϵ_P and ϵ_Q are the errors involved and x_i^min and x_i^max are the minimum and maximum limits of x_i^((t)). Disaggregation method proposed by Zhang et al. is shown in figure 3.



a: P-Q raw data
b: P-Q data and power angle boundaries by cluster
c: Signature vector of individual cluster
d: Actual signature vector after disaggregation

Fig.3. Disaggregation structure of the proposed algorithm [25]

Fig.2.2 Disaggregation structure of the proposed algorithm [25].

The algorithm was implemented in MATLAB 2015b. Public dataset- Pecan Street database was used as input raw data. Accuracy of 80% for main load categories and F-measure classification metric of 59-81% were achieved using this method.

The work was focused from utility point of view so as to investigate loads that affect power quality, deduce critical loads like electric vehicle charging etc.

Electricity usage profile disaggregation of hourly smart meter data using k-nearest neighbours algorithm [26]

In 2018 Zhao et al. proposed supervised K-Nearest Neighbours (KNN) based energy disaggregation method for 15min to 60min granularity of smart meter data [26]. The method used features like statistical measures of energy signal, appliance time usage profiles and reactive power consumptions.

Total energy consumption within the ith time interval is given by (7).

$$W_{Pi} = \sum_{m \in M} W_{Pmi} + n_i \quad (7)$$

where Wpmi is the energy contribution by the mth appliance, M is the total number of appliances and n_i is the noise due to measurement error and unknown appliances. Features were extracted by training process using sub-metering data. Relative standard deviation was used to verify the quality of each feature extracted. During testing phase, distance-d(.,.) between each hourly test data y and all samples of training data xi were calculated. Minimum distance calculated as per (8) is calculated for all possible candidates and selected neighbours x classified appliances.

$$d_y = min\{d(y, x_1); d(y, x_2); \dots; d(y, x_k)\} \quad (8)$$

Schematic of the algorithm proposed in the above work is shown in figure 4.

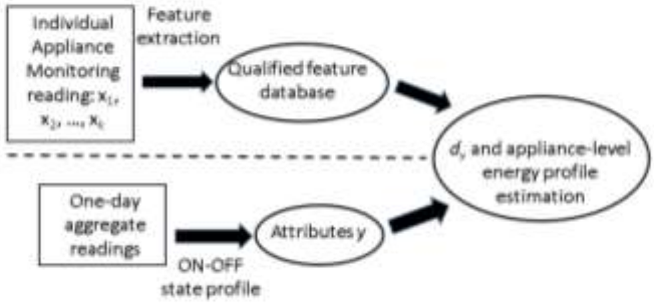


Fig.4. Schematic of the proposed algorithm based on KNN [26]

The algorithm was tested on REDD, REFIT and AMPDs public datasets. It was found that the methodology could disaggregate around 62% of the daily energy consumption with noisy data.

Unsupervised algorithm for disaggregating low-sampling-rate electricity consumption of households using device usage estimation algorithm [27]

Howlweger et al. proposed an unsupervised person-centric load disaggregation algorithm called Device Usage Estimation (DUE) algorithm based on Markov model [27]. The method was based on activities of inhabitants by grouping appliances together based on common activities. General household data and energy measurements were taken as input.

With the assumption that children below 10 years of age had little energy consumption, activity chains for individuals above 10 years were generated with the help of Markov model. Once characteristics of the household and probabilities of activities were known, appliances that could be ON were predicted with the help of aggregated load pattern. Using this method, power consumptions of eight categories of devices were estimated. Various device categories were cooking, entertainment, fridge, heating, housekeeping, ICT, light and standby.

According to Markov chain, if a system has x∈S states the probability of switching from state Si to Sj element of transition matrix is given by (9).

$$a_{ij} = p(x^t = S_i | x^{t-1} = S_j) \qquad (9)$$

Initial probability distribution is given by (10).

$$\pi_i = p(x^0 = S_i) \qquad (10)$$

Elements of emission matrix, where y is the external variable through which system can be observed O_kare the multiple states of y, is given by (11).

$$b_{ki} = p(y^t = O_k | x^t = S_i) \qquad (11)$$

In the proposed algorithm, transition matrix and initial probability matrices were dependent on type of the day i.e. weekday or holiday and on household characteristics like employment state, age group etc. General workflow of the algorithm is shown in figure 5.

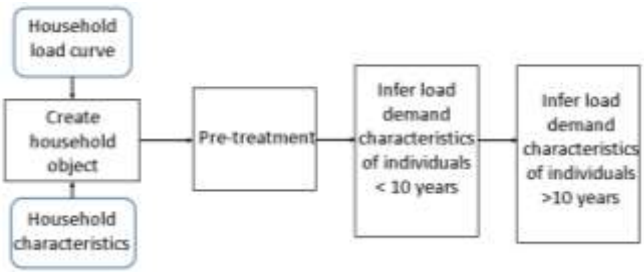


Fig.5. General workflow of load disaggregation using DUE algorithm [27]

Based on the household load curve and characteristics, household object categories were generated initially. Then pre-treatment process was conducted to remove standby loads and refrigerator loads. The resultant data were used to extract person-centric demand characteristics of individuals above and below 10 years of age.

The algorithm was benchmarked against four methods namely combinatorial optimization, factorial hidden Markov model, graph signal processing and discriminative disaggregation via sparse coding. Test datasets used were ECO, SMARTENERGY.KOM, and UK-DALE. Data sets with sample rates of 15min were used for the proposed algorithm. It was concluded that supervised algorithms outperforms unsupervised ones. Prediction uncertainty for DUE method was under 20% and did not suffer from computational limitations.

An optimisation-based energy disaggregation algorithm for low frequency smart meter data [28]

An optimization-based energy disaggregation method was proposed by Rottondi et al. in 2019 [28]. The work focused on two drawbacks of supervised sparse optimization disaggregation algorithm proposed by Piga et al [29]. The original algorithm was based on assumption that power consumption of individual devices were piecewise constant over time. This assumption cannot hold true for low sample rate smart meter data. Also the method proposed by Piga et al. did not take into account the presence of unknown devices. Rottondi et al. modified the algorithm to so as to take into account low rate aggregated smart meter data and unknown devices.

Energy disaggregation problem as a blind identification problem for N devices problems can be modelled as (12) and (13).

$$y(t) = \sum_{i=1}^{N} y_i(t) \qquad (12)$$

where:

$$y_i(t) = \left[B_i^{(1)} \ \dots B_i^{(C_i)}\right]\begin{bmatrix}\theta_i^{(1)}(t)\\ \dots \\ \theta_i^{(C_i)}(t)\end{bmatrix} + e_i(t) \qquad (13)$$

where y_i (t) is the power demand of ith device at time t, C_i is the total number of operating modes of the device, B_i^((j)) is the device power demand at the jth operating mode and e_i (t) is the intrinsic modelling error. θ_i^((j)) (t) can be either 0 or 1.

Disaggregation algorithm as a least-square minimization problem can be represented as (14) and (15).

$$\min_{\theta_i^{(j)}(t)} \sum_{t=1}^{T}\left(y(t) - \sum_{i=1}^{N} \hat{y}_i\,(t,\theta_i)\right)^2 \qquad (14)$$

with:

$$\hat{y}_i(t,\theta_i) = y_i(t) - e_i(t) = \left[B_i^{(1)} \ \dots B_i^{(C_i)}\right]\begin{bmatrix}\theta_i^{(1)}(t)\\ \dots \\ \theta_i^{(C_i)}(t)\end{bmatrix} \qquad (15)$$

To account for change in device consumption level (non-piecewise-constant energy consumption), Rottondi et al. added a penalty to the quadratic programming model proposed by Piga et al. as (16).

$$\min_{\theta_i^{(j)}(t)} \sum_{t=1}^{T}\left(y(t) - \sum_{i=1}^{N} \hat{y}_i\,(t,\theta_i)\right)^2 \sum_{\substack{t=1\\ i=1}}^{\substack{t=T\\ i=N}} \alpha_i x_i(t) \qquad (16)$$

where α_i is the weight of the ith device and x_i (t) is 1 if ith element changes the consumption level in interval-t. In order to account for unknown devices, Rottondi et al. addedmixed integer constraints that limit the length of the activity period and maximum consumption of appliances in set N.

The algorithm was implemented in AMPL and solved with Gurubi solver. It was benchmarked against two state-of-the-art disaggregation methods namely combinatorial optimization and factorial hidden Markov model. Test datasets used was UK-DALE. Data sets with sample rates ranging from 5min to 60min were used as raw data. It was concluded that the proposed algorithm could solve load disaggregation problem for low sample rate electric signals in the presence of unknown loads.

Other Recent Relevant Works

There are a many research contributions reported recently on NILM solutions for aggregated electrical signals with low granularity. Table 2.1 summarizes some of the relevant works.

CONCLUSIONS

An elaborate literature survey was carried out in the field of non-intrusive load monitoring problem with an emphasis on disaggregation solutions for low-rate smart meter data. Salient observations are:

1. The recent advancements in the field of smart meters and internet of things (IoT) has increased the prospects of large scale deployment of non-intrusive load monitoring (NILM).
2. Though several variants of machine learning algorithms have been employed by researchers, no single method offers load disaggregation solution to all types of appliances.
3. Due to the presence of different makes of a given appliance and due to the possibility of different patterns of operation by a user, development of generic appliance models is a formidable task.
4. Since supervised methods require off-line training of classifiers, it is difficult to implement them in real-time due to the unavailability of an updated appliance signature database.
5. Owing to the consumer privacy and economic concerns, low rate aggregate energy data is gaining more popularity.
6. However identifying low power consumer appliances exhibiting similar power consumption characteristics and multistate appliances is a challenge for low rate data.
7. Since unsupervised disaggregation methods do not require a priori training, there is no requirement for sub-metering of individual appliances. They are economical and thus appears to be a good choice for real time NILM implementation.

An optimal non-intrusive load monitoring system should be able to accurately identify and disaggregate in near real times, all constituent appliances of a household using standard smart meter measurement data in the most economical way. It should identify all types of appliances regardless of their category, make, size and the manufacturer.

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