An Approach for Unsupervised Non-Intrusive Load Monitoring of Residential Appliances

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***Abstract*— Non-Intrusive Load Monitoring (NILM) refers to the analysis of the aggregate power consumption of electric loads in order to recognize the existence and the consumption profile of each individual appliance. In this paper, we briefly describe our ongoing research on an unsupervised NILM system suitable for applications in the residential sector. The proposed system consists of the typical stages of an event-based NILM system with the difference that only unsupervised algorithms are utilized in each stage eliminating the need for a pre-training process and providing wider applicability. In the event detector, a grid-based clustering algorithm is utilized in order to segment the power signals into transient and steady-state sections. Macroscopic features are extracted from the detected events and used in a mean-shift clustering algorithm. The system is tested on the publicly available BLUED dataset and shows event detection and clustering accuracy more than 98%. The system also shows possible disaggregation up to 92% of the energy of phase A of the BLUED dataset. Moreover, the system has been utilized in an energy-disaggregation competition held by Belkin and achieved a score within the top ten results with disaggregation of more than 93% of the total time.**

***Index Terms*— Inverse Load Reconstruction, Unsupervised Non-Intrusive Load Monitoring (NILM), Grid-based Clustering, Mean-Shift Clustering, BLUED Dataset**

I. INTRODUCTION

Energy disaggregation becomes more and more important not only to residential consumers but also to power companies as well as appliance manufacturers. Many residential consumers lack a good understanding of their usage of energy or even the consumption of individual appliances [1]. Power companies require accurate estimates about future energy usage in order to handle more efficient energy generation strategies such as load-dependent energy generation, smart-grids, dynamic pricing models, or even to find more efficient energy conservation approaches. Appliance manufacturers can benefit from a detailed usage pattern of their appliances in order to provide more energy-efficient appliances or new power applications such as home automation, activity sensing, and health care.

Electrical loads can be monitored either in a distributed approach where each appliance has its own sensor or by disaggregating the building-level energy consumption profile in an approach commonly referred to as Non-Intrusive Load Monitoring (NILM). NILM systems disaggregate the electrical signal measured from a single or a limited number of metering points, thus, providing more reliability as a result of the reduced metering points and less cost due to the reduction in the utilized hardware. Research on NILM flourished during the last decade in three directions, namely, selection and extraction of features for different loads, development of detection and classification algorithms, and acquisition of power datasets that assist in development and evaluation of NILM systems. A good review of existing NILM approaches is found in [1–3].

NILM systems are categorized into event-based and non-event-based approaches. Event-based NILM systems rely mainly on the detection and classification of events within the aggregate electrical signal. Furthermore, NILM systems are categorized into supervised and non-supervised approaches depending on whether or not they require a training process prior to deployment on a target building. In contrast, unsupervised NILM systems do not required pre-training and are, therefore, expected to have a wider applicability and even less intrusion.

In this paper, we describe our ongoing research on a completely unsupervised event-based NILM system. A brief description of the algorithm in each stage is provided together with results of application on two power datasets. This paper is organized as follows. Section II introduces the event-detection stage. In Section III and Section IV, we describe the event clustering stage and the features selected for this stage. Section V briefly describes the transition matching process and estimation of the energy consumption of each load. Experiments are described in Section VI together with their results. Finally, Section VIII concludes this paper.

II. EVENT DETECTION

In the event detection stage, the electrical signal is segmented into transient Ψ and steady-state Π sections. In contrast to the conventional change-point detection, the proposed event detector is capable of accurately defining the time limits of each transition interval Ψ. Accurate detection of the change interval is crucial for extracting appliances' signatures from their transient behavior.

In this event detector a clustering algorithm is repetitively applied on overlapping intervals of the continuously streaming real and reactive power signals at frequencies between 1Hz to 60Hz. Therefore, the event detector is the performance bottleneck of the proposed system. In order to reduce the computational complexity of this stage, we follow two approaches. First, the detection process is applied on the logarithmically transformed signals P_l and Q_l of the raw real P and reactive

Q power signals based on the function

$$X_l = \begin{cases} \ln(X) & X > 0 \\ 0 & X = 0 \\ -\ln(-X) & X < 0 \end{cases} \quad (1)$$

where $X \in \{P, Q\}$. With this transform, the event detection is performed on a narrower power range resulting in reduced computation time. The transform also helps in suppressing high fluctuations in higher power ranges. An offset may be added to adopt the transform to a suitable operating point.

Second, we utilize a grid-based clustering scheme which is closely related to density-based clustering but rather less computationally expensive. Thus, the event detector preserves a real-time processing of the signals even though the whole NILM system is based on batch-processing due to the event clustering stage. In the following, the event detector is described using a two-dimensional signal of the real P and reactive Q powers. However, the detection algorithm is applicable to higher dimensions and it has also been tested on a one-dimensional signal of the real power P only.

Given a interval $[t_i, t_{i+n}]$, where t_i is the time of the i^{th} instance, the transformed real $P_l\,[t_j]$ and reactive $Q_l\,[t_j]$ power signals are projected on the P_lQ_l-plane where $t_j \in \{t_i, t_{i+1}, t_{i+2}, \ldots, t_{i+n}\}$. In the resulting P_lQ_l-plane, steady-states Π are represented as clusters while transients Ψ as well as noise are found as scattered points or outliers. Figure 1 shows an example of two appliances from the BLUED dataset plotted on P_lQ_l-plane.

For a clustering-based event detection two steps are required. First, the interval $[t_i, t_{i+n}]$ must be selected such that it contains exactly one transient event and two steady-states. The second is an efficient, noise-aware, low computationally demanding clustering algorithm that can be applied repeatedly on the P_lQ_l-plane to extract the transient event as the noise and the steady-states as the clusters.

A sliding window with increasing width is used to satisfy the first requirement. The window size is increasing sequentially (by increasing n) while applying the clustering algorithm on each incremental step. The interval is defined by the first time two clusters are detected. This further requires that the clustering algorithm does not assume any prior knowledge about the number of clusters.

In the utilized grid-based clustering algorithm, the P_lQ_l-plane is divided into equally sized rectangular pins. The plane is then treated as a binary image and is searched for connected objects (dense areas). Each object's value is the sum of all bins' values that belong to the object, and each bin's value is in turn the number of data points that belong to the bin. The algorithm requires two parameters, namely, the bin size ϵ and the cluster threshold $minPts$. These two parameters are mapped to physical quantities as follows. For the value of the bin-size in the real power dimension:

$$\Delta P_{min} = e^{2\times\epsilon_P + ln(P)} \quad (2)$$

where ΔP_{min} is the minimum change assumed for an event at a working point P. The $minPts$ is mapped to the minimum required length of a steady-states as:

$$minPts = \Delta T_{min} \cdot f_s \quad (3)$$

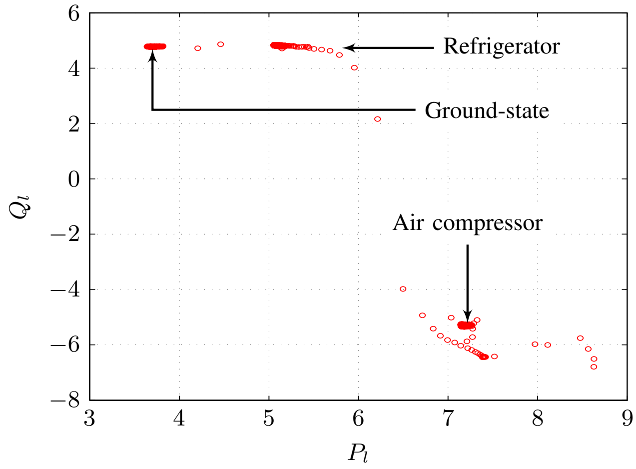


Fig. 1: The P_lQ_l-plane of a signal from the BLUED dataset [4] that includes two loads.

where ΔT_{min} is the minimum length of a steady-state and f_s is the sampling frequency of the real and reactive power signals. Connected objects with object-values greater than the threshold $minPts$ are considered clusters that represent steady-states while other objects are noise that result from the transients. Worth noting is that the developed algorithm includes a further refinement and verification steps that can handle special cases such as simultaneous events that are apart from each other by a value less than ΔT_{min}. Also, the parameter $minPts$ is increased to account for high fluctuations if detected.

Figure 2 shows a sample signal from Belkin's dataset with a sampling frequency of 6 Hz. The figure also visualizes two features in the detected events (highlighted with blue circles) upon application of the event detection algorithm with $f_s = 6$ Hz and $minPts = 10$ samples (i.e. $\Delta T_{min} = 1.67$ seconds). The first half of the signal shows an example of off-on simultaneous events. Off-on simultaneous events are detected even though in some cases the steady-state length is 600 ms.

The second half shows an example of varying steady-states where Π_{12} and Π_{14} follow a sinusoidal behavior while Π_{13} has a wide and changing noise pattern. The figure shows the advantage of the dynamic bin size adaptation in handling these steady-states. Observable from the figure, however, is that high noise values (± 50 Watts) led to an inaccurate detection as observed in Ψ_{12}.

III. Feature Extraction

In this stage, features are extracted from each transient section. Selected features are the power change $\Delta\Psi$ and the transition spike $\delta\Psi$. Each feature is computed on both the real P and reactive Q power signals as follows

$$\Delta\Psi_i^X = \Psi_i^X(N_i^\Psi - 1) - \Psi_i^X(0) \quad (4)$$

and

$$\delta\Psi_i^X = \mathrm{sign}(\Delta\Psi_i^X)\left(\max_n \Psi_i^X(n) - \min_n \Psi_i^X(n)\right) \quad (5)$$

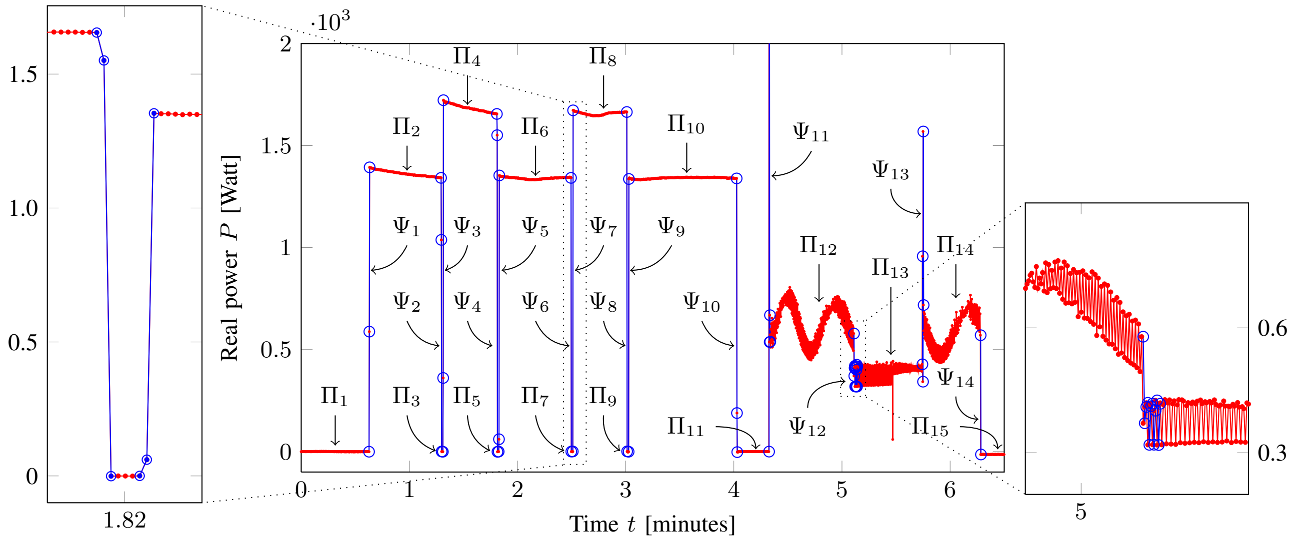


Fig. 2: The application of the event detector on 6 Hz power signal from Belkin energy disaggregation competition on Kaggles platform [5] with $minPts = 10$. Highlighted in blue circles are the detected events. Shown on the left is an example of detected off-on event. On the right is an example of noisy steady-states and their effect on the detection.

where $X \in \{P, Q\}$ and N_i^{Ψ} is the number of data samples in the transient section Ψ_i. This results in a four dimensional feature vector. The set of all vectors are then fed to the clustering stage.

IV. Events Clustering

In the clustering stage, events are grouped into separate clusters according to their extracted features. Since the number of underlying appliances is not known in advance, we utilize a non-parametric clustering algorithm, namely the mean-shift clustering scheme. The mean-shift clustering algorithm has the advantages that it is non-parametric, independent of the underlying distribution, and implicitly includes a mode-seeking algorithm. Recently, mean-shift clustering has been proposed for application in NILM systems and was proved to provide even better results than the k-means algorithm in special cases [6]. We utilize a simple kernel function such as

$$K(\boldsymbol{\theta}) = \begin{cases} 1, & \text{if } \|\boldsymbol{\theta}\| \leq \lambda \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

where λ is the kernel bandwidth.

V. Transition Matching

In the transition matching stage, on- and off-events belonging to the same appliance are grouped together so that the whole operation interval of each appliance can be inferred. In this work, we only propose an initial transition matching stage that can be used to reduce the search space for further matching processes but does not guarantee high disaggregation ratios except in special cases. The matching process in the proposed system is based on the ground-state detection.

A ground-state is a state during which no detectable appliance is operating. In the implemented NILM system, the ground-state is detected as the steady-state with the lowest power consumption level in a signal with the duration of at least one day. We observed that in the residential data there are several times when the occupants have limited activity. Such low-activity periods include small number of simultaneously operating loads and are, therefore, utilized in self-training the NILM system for transition matching.

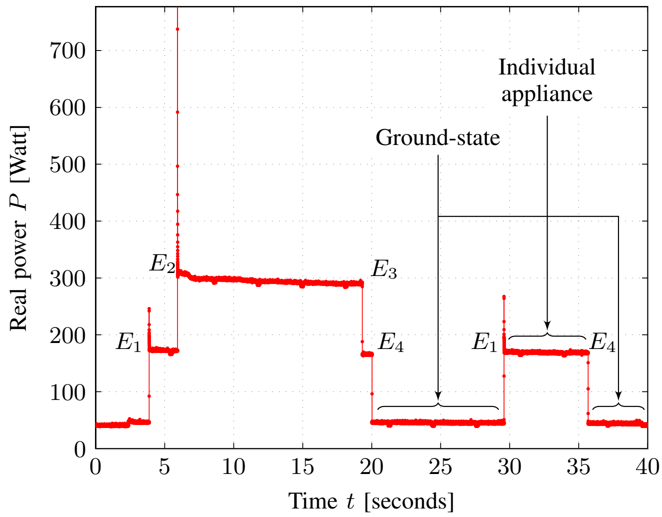
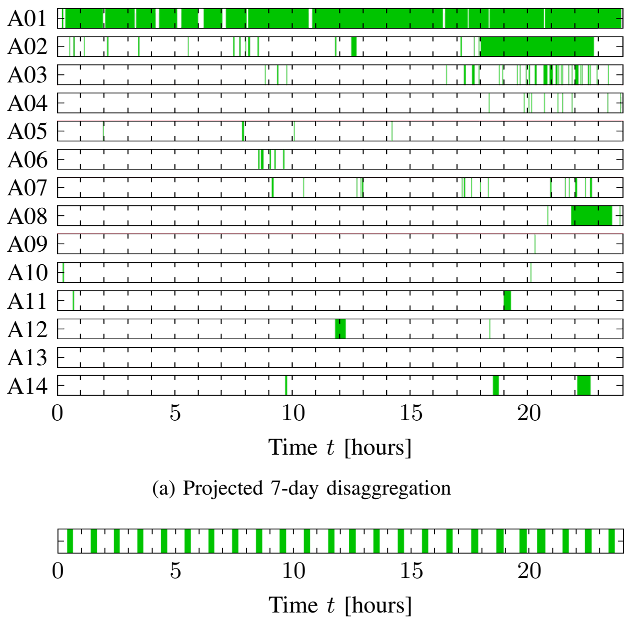


Fig. 3: A pair of on- and off-events (right E_1 and E_4) surrounded by ground-states belongs to the same appliance. Events are labeled E_i where i is the cluster index based on the output from the event clustering stage.

According to the definition of the ground-state, if a pair of on- and off- events are surrounded by ground states (i.e. a ground-state before the on-event and another after the off-event) then these two events must belong to one appliance and the interval in between also belongs only to that appliance.

Figure 3 shows an example of a solely-operating appliance detected in between two ground-states. In the first iteration, the right pair of on- and off-events (E_1, E_4) are matched and considered switch-on/off events. Once these two events



(a) Projected 7-day disaggregation

(b) Refrigerator 1-day disaggregation

Fig. 4: Operation intervals of disaggregated appliance from phase A of the BLUED dataset [4].

are matched, the matching is triggered again based on the matching that occurred in the previous iteration. In the second iteration, given that E_1 is matched to E_4, then the on-event E_2 is matched with only remaining off-event E_3. This is repeated until no more matching is possible.

VI. Experiments and Results

The event detector is tested on the publicly available BLUED dataset [4] and the power dataset provided by the consumer electronics manufacturer Belkin in its energy disaggregation competition [5] held on the Kaggle's platform.

TABLE I: Event detection results

	TPP	FPP	Events E
Phase A	98.5%	0.55%	886
Phase B	70.5%	8.75%	1579

Table I shows the event detection results of both phases of the BLUED dataset. The True Positive Percentage (TPP) and the False Positive Percentage (FPP) represent the second detection metric defined in [7]

Figure 4a shows disaggregation results of the NILM system on the BLUED dataset. The BLUED dataset has 7-day long measurements. In the figure, we projected all operation intervals of disaggregated appliances into a single 24-hours day. Shown results belong to phase A only and has 14 detected appliances where shaded green areas represent their intervals of operation. $A02$ represents two lights, bed room lights and bathroom downstairs lights because the system was not able to disaggregate these two load due to the similarity in their signatures. The figure also shows the low-activity during the time period [0, 7] hours as expected. Such low-activity periods are utilized in self-training the NILM system using individually operating appliances. The total disaggregation reported by the system is 92% of the total energy. Since disaggregated data is not readily available with the BLUED dataset, disaggregation results from our NILM system on BLUED are not yet verified. Developing the disaggregation data for BLUED is among our future work.

Appliance $A01$ is the refrigerator. As observed, its operation does not depend on the time of the day simply because it is a background appliance. Figure 4b shows a single-day disaggregation of the refrigerator. The figure shows the clear periodic behavior of the load which directly indicates that it has an on-off controller. Using this information together with characteristics from the power signals (for example being resistive, capacitive, or inductive) can lead to an identification of the category of appliance. Therefore, behavioral analysis of disaggregated appliances is also among our planned future work in order to develop an unsupervised NILM system with appliance identification.

Finally, we participated in the energy disaggregation competition held by Belkin on the Kaggle platform using the developed NILM system with minor modifications. The disaggregation results were in the 5$^{\text{th}}$ position when evaluated on the public folder, and the 6$^{\text{th}}$ on the private folder on the last day of the competition 30$^{\text{th}}$ of October, 2013. Results showed a successful disaggregation of 93.41% of the total time.

VII. Future Work

As previously mentioned, this is an ongoing research and our work on non-intrusive monitoring is still in progress. Our planned future work is divided into three directions. On the algorithmic level, we can clearly see several chances for enhancement either in the individual stages or the complete NILM system. Second, we target continuous evaluation of the proposed system on larger power dataset including of course verification of the disaggregation results of the BLUED dataset which is currently in progress. Finally, in order to apply the system to a larger number of loads we are also working on extending the proposed system to include high frequency features.

VIII. Conclusion

We have developed a completely unsupervised event-based NILM system suitable for and tested on residential datasets. In this paper, we briefly described the algorithm utilized in each stage. We also provided results of the application on the BLUED dataset with event detection and classification up to 98% of the total events and a complete disaggregated up to 92% of the total energy of the BLUED dataset. Application on the Belkin's power dataset resulted in disaggregation of more than 93% of the total time. In a future work, we are planning to provide disaggregation data of the BLUED dataset together with application of our NILM system on its both phases.

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