Transient Signature Detection of Appliances for Household Energy Consumption Disaggregation

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***Abstract*—Even with advances in smart grid technology and a growing demand for cost-effective energy consumption, detailed information about energy usage is often not available for residential electricity consumers. One reason is that household energy usage is monitored at no more than a single point by the utility, only providing information on the aggregate power consumption. In this paper, we attempt to disaggregate energy usage data into specific appliances from single-point sensing measurements. Our method involves extracting turn-on and turn-off signature windows from time-series real and reactive power data to obtain transient characteristics of each appliance. We focus on determining the appropriate window size for each appliance in order to capture unique signatures. We present the results of our approach on a publicly available dataset.**

I. Introduction

The objective of residential non-intrusive load monitoring (NILM) is to monitor the major loads in a home from a single-point. The alternative is to monitor each appliance individually, however, this scheme typically adds significant cost. Therefore, the challenge with NILM is to accurately disaggregate household energy consumption into the individual appliance level with data from single-point measurements.

Prior research in the area of NILM has focused on the use of aggregate power consumption patterns as features to identify what appliance is being used and how much energy it is consuming. For example, the authors in [1] discuss various approaches in NILM, including detecting changes in steady-state power measurements and characterizing them as different events. Some challenges reported by the authors include different loads not exhibiting unique signatures in the 2D feature space and the difficulty in determining steady-state features due to turn-on transient noise. Some recommended advanced techniques are to include the 3rd order harmonics as a feature and using turn-on transients for event detection. The methodology in [2] and [3] follows a similar strategy, however, the training and test data are manually generated, resulting in a clean dataset that may not be representative of real household energy usage patterns. Furthermore, the classification can become challenging if the number of appliances in the home is large. Additionally, the signature of some appliances may drift or vary over time due to operating conditions and the mode in which they are used.

In this paper, we present a method that focuses on extracting turn-on and turn-off signature windows to obtain transient characteristics of each appliance. The transient characteristics are observed from the difference of two moving average windows from time-series real and reactive power data. We focus on determining the appropriate window length for each appliance in order to capture unique signatures. We present the results of our approach using a publicly available dataset from the Belkin Energy Disaggregation Competition on kaggle.com [2]. The dataset and methodology are described in detail in Section II. Section III describes the approach for extracting signature windows for each appliance from the training data. Section IV describes the cross-validation procedure using the training data. Section V describes application of our approach to the test data. Finally, Section VI discusses results and ideas for future work.

II. Data and Methodology

In this section, we describe the dataset that was used and our methodology for detecting appliances in the test data. Because the set of appliances in each home includes multiple small devices with similar steady-state load characteristics, our methodology focuses on identifying the unique features when a device turns on and off (the transient periods). Out of approximately 37 appliances per home, only a small subset exhibits steady state features that allow discrimination from other appliances or background noise.

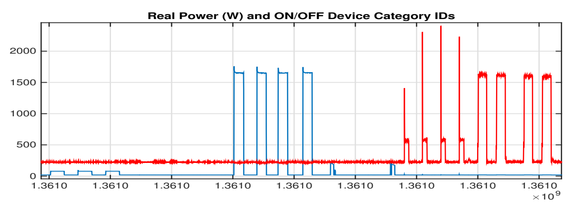
A. Dataset

In this paper, we utilize the complete dataset available from kaggle.com, provided by Belkin Energy [2]. The dataset is publicly available on the competition website and contains the first five harmonics of rms voltage and current on two phases for four households (labeled H1-H4). The dataset also contains high frequency noise (EMI) data for each household, but is not required with our approach (see further discussion in Section VI). Although both training and test datasets are provided, only the training data provides labels and corresponding timestamps for each appliance. Table I shows the number of distinct appliances in each home an the number of training and test sets provided.

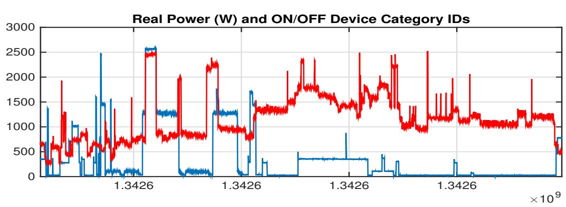
TABLE I
NUMBER OF DISTINCT APPLIANCES AND DATASETS FOR EACH HOME

Home No.	Appliances	Training	Test
H1	38	6	4
H2	37	4	4
H3	37	3	4
H4	36	2	4

The training sets consist of manually generated power consumption data for each appliance in each home. The training data is a time-serires where only one appliance is switched on at a time, although background noise can be present from untagged appliances. Tagging labels in the training data are also provided by Belkin, however, these are not always precise enough to correctly identify device on and off times. Tagging label correction is discussed in Section III. Fig.1 shows an example of both training and test data from H2. The observations recorded in each training and test set cover approximately 24 hours.



(a) Training



(b) Test

Fig. 1. Example of (a) training and (b) test data from Home 2. Real power consumption is shown for both phases.

B. Methodology

Our goal is to develop an interpretable yet effective classification approach. It can be observed from Fig. 1 (b) that the test data is the aggregated load of multiple appliances. Therefore, at any given time, it is not possible to determine which appliances are operating by using only the level of power consumption. However, when an appliance is turned on or off, a step change is produced in real and reactive power. By comparing the average power consumed before and after these transient events, we can calculate averaged power differences, facilitating discrimination among appliances. For this reason, our methodology focuses on detecting unique turn-on and turn-off signatures in the power differences domain for each appliance.

The first step is to extract transient signature windows for each appliance and is accomplished by converting P and Q

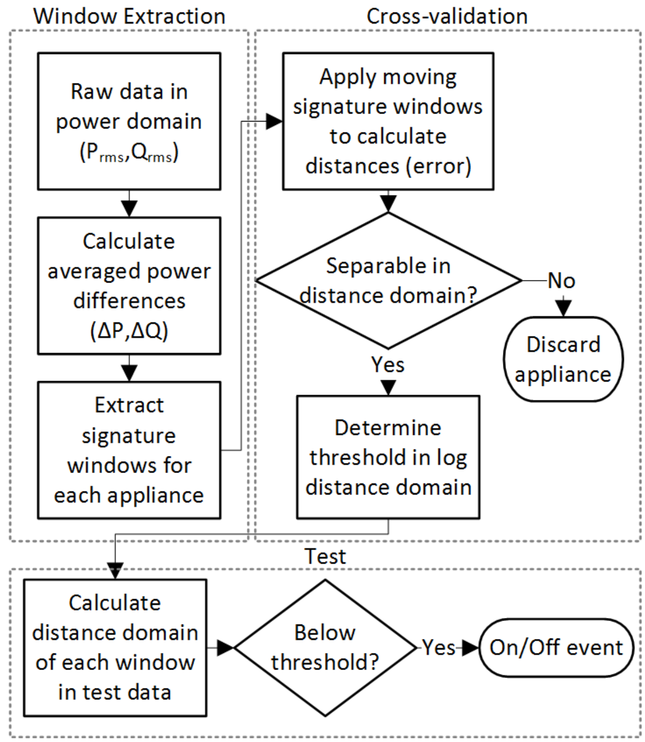


Fig. 2. Flow chart of proposed methodology. The procedure is separated into window extraction, cross-validation, and application to test data.

domain into the differences domain by taking the difference of two moving average windows . After P and Q differences are calculated, transient signature windows are extracted for each appliance. This procedure is explained in detail in section III.

Once transient signature windows are extracted for each appliance event in the training data, cross-validation is performed to determine if the signature windows are unique. This procedure is explained in detail in Section IV.

III. TRAINING - SIGNATURE WINDOW EXTRACTION

This section describes how transient signature windows are extracted by using the real and the reactive power differences. In particular, a pair of turn-on and turn-off signature windows are trained for each event of each appliance. The following sections describe how training the signature windows is dependent upon the shape of the load.

A. Load Types

First, the appliances are categorized into three load types based on their load shape in P and Q. The types include rectangular, non-rectangular, and cyclic loads:

1) Rectangular loads: These type of loads consume constant power when operating and their transient period is characterized by a sharp transition from zero to rated power consumption. Their load shapes are generally rectangular and consist of primarily resistive loads, such as lights, heaters, and kettles. Some inductive

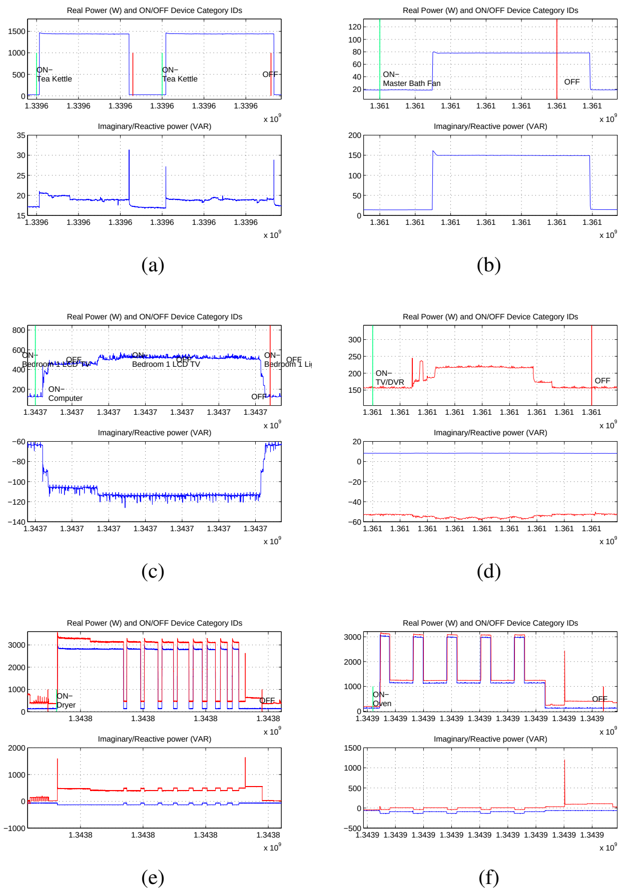


Fig. 3. Load Types (a) Tea Kettle, (b) Master Bath Fan, (c) Computer, (d) TV, (e) Dryer, (f) Oven.

loads, such as small fans, also exhibit this load shape. A short duration window consisting of the real and the reactive power differences are used to detect these loads.

2) Non-rectangular loads: These type of loads have a longer transient period when turning on and include computers and TVs. Their transient period is characterized by a stepwise transition from zero to rated power consumption. Although the power consumed may vary based on how the device is operated, the turn-on signatures can be unique, allowing discrimination against other devices. These type of loads require a longer window length to capture the unique transient shape.

3) Cyclical loads: - The amount of real or reactive power consumed by these loads change depending on the cycle of their operation. Dryer, oven, and washers are included in this category. However, because they operate on set cycles, there are only a few possible periodic load shapes they can follow. Two approaches are suggested to detect these type of loads; using multiple windows or detecting a notable landmark during the operation.

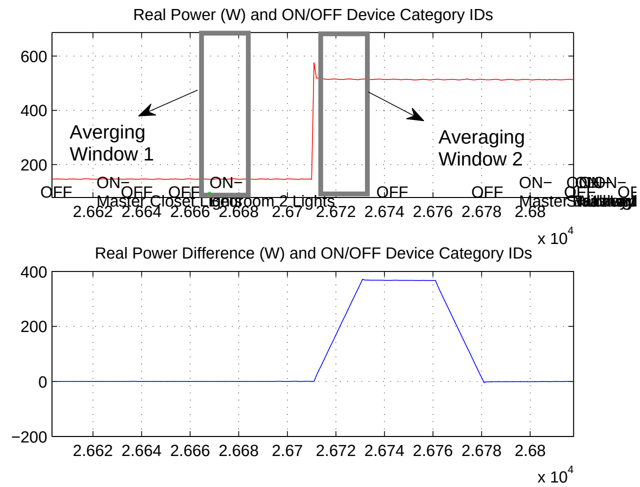


Fig. 4. Difference of two moving average windows to detect transient signatures.

B. Averaged Power Differences

Moving average differences are used to detect step changes in real and reactive power consumption. To train the windows, the real and the reactive power differences are calculated from two moving average windows. The average differences for real power $S_P(n)$ is defined as,

$$S_P(n) = \frac{1}{N}\sum_{k=0}^{N} P(n-k) - \frac{1}{N}\sum_{k=N+D}^{2N+D} P(n-k) \qquad (1)$$

where N is the window size and D is the distance between the two windows. The average differences for reactive power, $S_Q(n)$, is calculated using the same N and D. It should be noted that if a shorter window size is used, it is easier to distinguish events happening at the same incidence. However, the detector becomes less robust to noise.

Using the power difference, the mismatches in the tagging info and the actual event index are corrected. A threshold for the real power difference is set to indicate whether an event occurred, (event occurred if $|S(n)| >$ threshold). Then the corrected indexes are used as the actual event index instead of the tagging info provided in the raw data. On the top plot of Fig. 5, the tagging labels of the master bedroom lights do not align with the actual event incidence. The red markers in the bottom plot shows when the power difference is greater than the threshold; this index is used as the corrected tagging label. It should be noted that some appliances that consumes very small real or reactive power are discarded as they cannot be detected. For these appliances, using real and reactive power differences will cause false detections in the test data due to the effects of the noise.

C. Signature Window Extraction

After taking the power differences, the next stop is to extract the signatures for turn-on events and turn-off events. The windows are extracted using the corrected tagging labels. If an

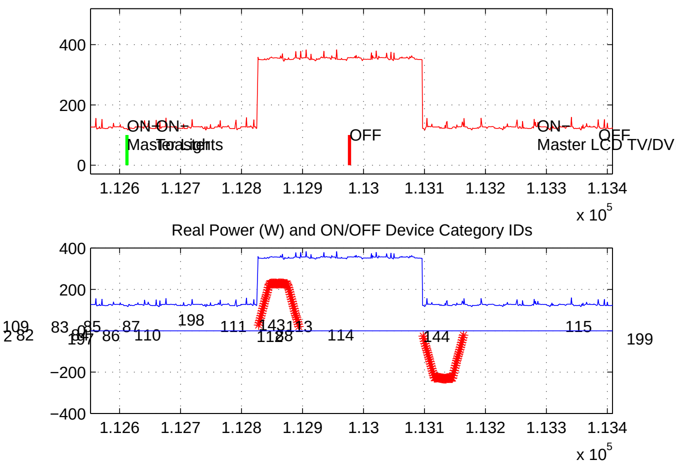


Fig. 5. Provided tagging labels are corrected in the power differences domain.

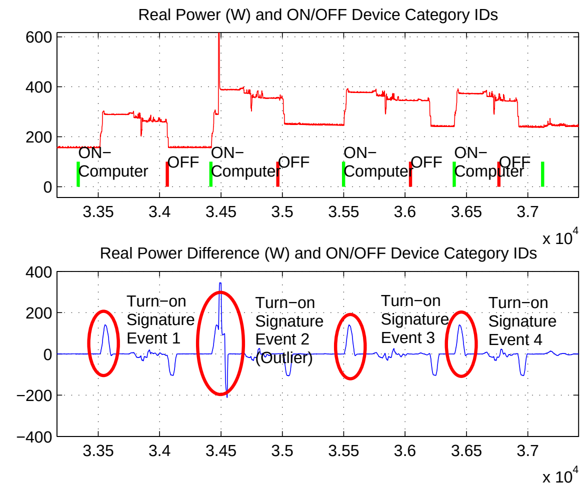


Fig. 7. Computer turn-on event outlier shown in the 2nd event.

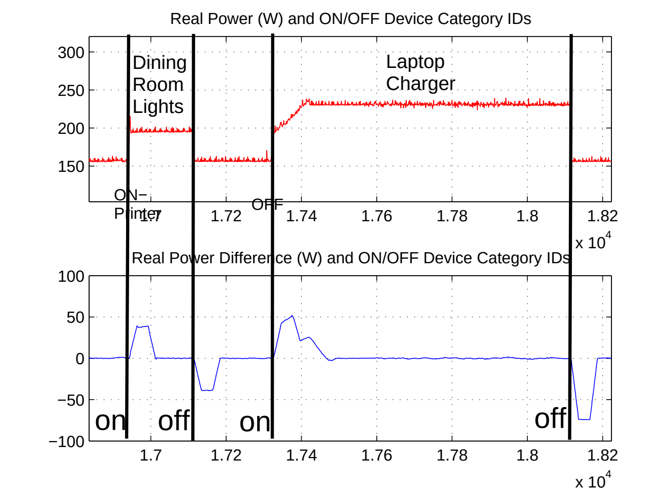


Fig. 6. Example of how choosing the appropriate window length can affect classification.

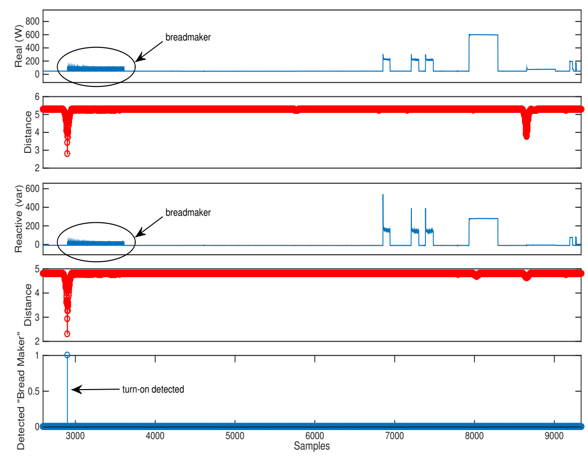


Fig. 8. Cross-validation of appliance "breadmaker" for two events in the training data.

appliance has longer transient characteristics (non-rectangular load shapes), longer window sizes are used to capture the entire unique transient period. For example, consider the dining room light and the laptop charger profile shown in Fig. 6. Both the appliances consume about 38 W at event incidence. However, the laptop charger then spends additional 38 Watts to fully turn on. Therefore, longer window lengths are needed to detect laptop charger than the dining room lights.

Insert windows used for cyclical loads.

Outlier detection is also held in this stage. Consider the four ON/OFF events of a computer as shown in Fig. 7. It is shown that when event 2 occurred, some background noise are introduced that affected the turn-on signature of the computer. In this case, the second event is regarded as an outlier and is not used in training the windows.

A typical rectangular load shape of is shown in Figure **??**. Many appliances turned out to have rectangular load shape and these appliances can be separated using real and reactive power consumption features. Figure **??** shows feature space of appliances that have rectangular load shape. The feature vector of each class are clustered together, implying that the real and reactive power features are sufficient for classifying most of the appliances.

IV. Validation

Although data is high resolution (and therefore high dimensional in number of rows), the majority of information unique to each appliance is concentrated to turn-on and turn-off signatures.

Prior to submitting our predictions, the

need figures as examples of P/Q domain, diff domain, distance domain, window shape (big subplot 3x3?)

show how signatures for small appliances, those of the same type in different locations, can produce different signature windows, allowing for separation.

include table of number of unique signature windows for each home

V. Test Data

- rules for on/off pairing

VI. Conclusion

The conclusion goes here. All insight gained from competition. Too many appliances, noisy test data, what is the benefit of identifying small appliances?, noise necessitates clear features (large distance). also high freqency domain for hard to identify appliances. you can get 20th w/ just P/Q alone.

A. Data Cleaning

Using this dataset, a lot of effort was put into cleaning the data. Specifically, the tagging information for appliance on off events was not precise enough to accurately extract on and off signatures windows automatically. However, if these event tags were generated correctly, event signature windows could be automatically extracted form the training data.

B. Load Types

discuss difficulty of classification based on load types:

-constant power - static: can be difficult if rated power is similar between two appliances, same for below. - resistive (lights, heaters, kettle) - P domain and rectangular mainly, can be separated in P domain only if turn on/off signature is unique or if rated power is not similar to others - resistive + reactive (rotating like fans) - Q is a feature to help classify; if P is not unique, but Q is, greatly increases classification - dynamic - cyclical (washer dryer) - require rules, ie. landmark detection

C. Tradeoffs

One of the advantages of this approach is that it is more interpretable as it follows intuition for detecting appliance on and off events. With the proposed approach, misclassifications can be traced back to the signature window length or detection thresholds. This is particularly true when compared to methods utilizing 'black box' predictive models such as artificial neural networks. Furthermore, the proposed approach as the ability for real time processing.

However, one of the primary drawbacks is that manual identification of appropriate window lengths is requried during training.

References

[1] C. Laughman, K. Lee, R. Cox, S. Shaw, S. Leeb, L. Norford, and P. Armstrong, "Power signature analysis," *Power and Energy Magazine, IEEE*, vol. 1, pp. 56–63, Mar 2003.

[2] http://www.kaggle.com/c/belkin-energy-disaggregation-competition.