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-ML

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.

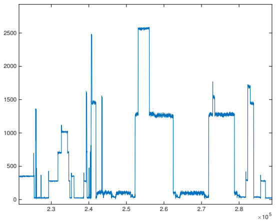
II. Data and Methodology

The objective is this.... because of this and the dataset, our methodology is specifically chosen for ...This section provides an overview of the dataset and a description of our methodology.

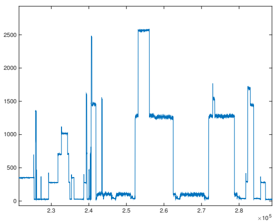
Because the dataset is representative of real world appliance usage data, and that we are trying to fine detect multiple appliances and not just major ones, we have chosen a specific methodology. If we are just detecting major appliances a different methodology can be used. Strategy is to detect when and appliance turns on and turns off as opposed to steady state characteristics. Out of 40 appliances per home, only a few exhibit steady state features that allow discrimination from background noise or other appliances.

A. Dataset

Show visualizations -data description -training data -figures show differences domain/power domain - explain reason for looking in difference domain - test data-multiple devices, and steady state, no changes -goal is to detect events on/off -for example, constant power loads, show no change, eg. light - needed to correct time stamps in order to accurately determine signature windows



(a) Training



(b) Test

Fig. 1. Example of (a) training and (b) test data from Home 4.

The dataset is publicly available on the competition website and contains voltage and current harmonics data for four households. The dataset also contains high frequency noise (EMI) data for each household, but is not required with our approach.

In this paper, we utilize the complete dataset available from kaggle.com, provided by Belkin Energy [2]. The set contains data from 4 homes (labeled H1-H4) consisting of both training and testing datasets. The training datasets are used to learn how each appliance in each home looks in terms of the EMI and harmonic signatures and build a model which can be applied to the test datasets for making predictions.

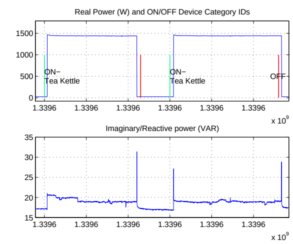
Two sets of data are supplied by Belkin Energy: Training and Test. Describe each one and show example figures of each. The training data consists of manually generated power consumption for each appliance at each home. These typically consist of only one appliance switched on at a time, although background noise is present from untagged appliances. Tagging labels are provided by Belkin, however, these are not precise enough to correctly identify device on and off times. A discussion for tagging label correction is presented in Section III.

For each home, the datasets include the first 5 harmonics of voltage and current measurements the FFT of the high frequency noise (captured every 1.0667 seconds). The sampling rate is f_s = 2 Mhz, which results in an FFT resolution of f_r = 244.14 Hz. The dataset for each home is composed of several files. For example, the data for H4 contains two training datasets and four testing datasets. The size and description of the files associated with each training and testing dataset are detailed in the tables below.

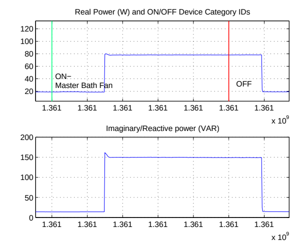
The observations recorded in each training and testing dataset cover approximately 24 hours. Therefore, the files in Table **??** for each training and testing dataset listed in Table I

TABLE I
NUMBER OF DISTINCT APPLIANCES AND DATASETS FOR EACH HOME

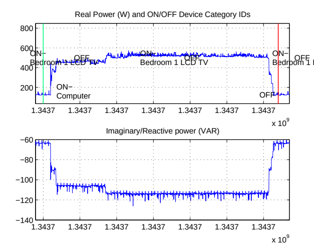
Home No.	**Appliances**	**Training Sets**	**Test Sets**
H1	38	6	4
H2	37	4	4
H3	37	3	4
H4	36	2	4



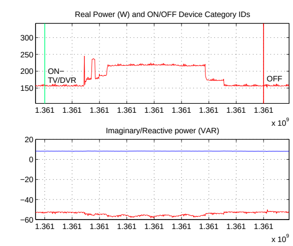
(a)



(b)



(c)



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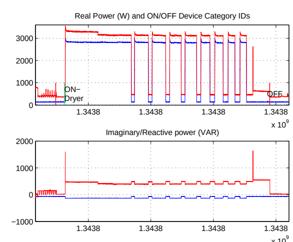

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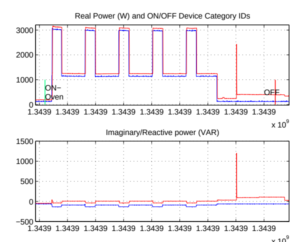

(f)

Fig. 2. Load Types (a) Tea Kettle, (b) Master Bath Fan, (c) Computer, (d) TV, (e) Dryer, (f) Oven.

have approximately the same sizes.

B. Methodology

-explain methodology - voltage/current harmonics to P/Q to differences to distances -and why we use this approach - include block diagram -goal is to automate, this task can be done manually, but too tedious -compare to previous and to data mining methods, ours is more interpretable -ability for real time processing

III. Training - Signature Window Extraction

This section concentrates on extracting transient signature windows by using the real and the reactive power differences. In particular, two ON/OFF signature windows are trained for each event of the appliances at each home. The following sections describe training signature windows depending on 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 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.

Based on these three general load shapes,

B. Average Power Differences

Average power differences are used to detect step changes in real and reactive power consumption. Now 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 shorter window size is used, it is easier to distinguish events from other 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

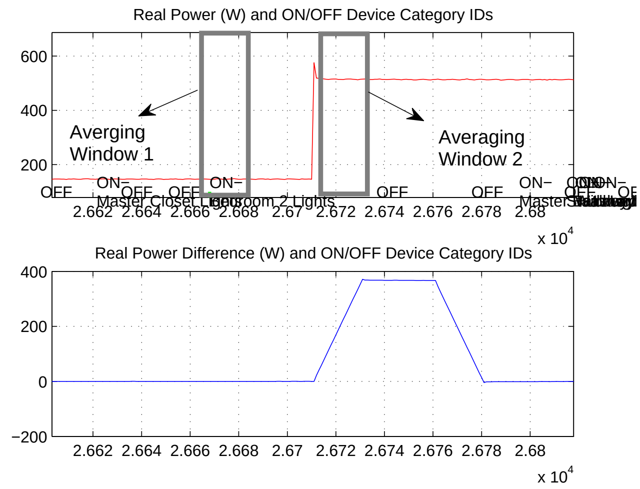

Fig. 3. Two Moving Average Windows.

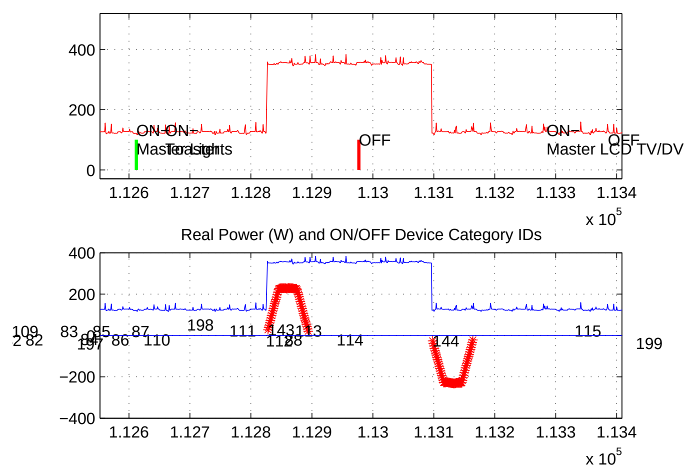

Fig. 4. Tagging Info Correction.

the real power difference is set to indicate whether an event occurred, (event occurred if $|S(n)| >$ threshold). Then this corrected indexes are used as the actual event index instead of the tagging info provided. On the top plot of Fig. 4, the tagging info of the master room 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 and this index is used as the corrected tagging info. It should be noted that we discarded some appliances that consumes very small real or reactive power. For these appliances, using real and reactive power differences will rather cause more false alarms in the test data due to the effects of the noises.

C. Signature Window Extraction

After taking the power differences, the next stop is to extract the signatures for on-events and off-events. The windows are extracted starting from the corrected tagging info. If an appliance has an longer transient characteristics (non-rectangular

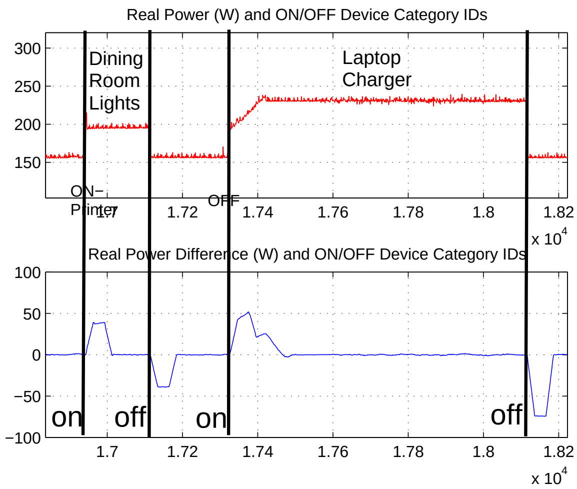

Fig. 5. Simple Distribution Feeder.

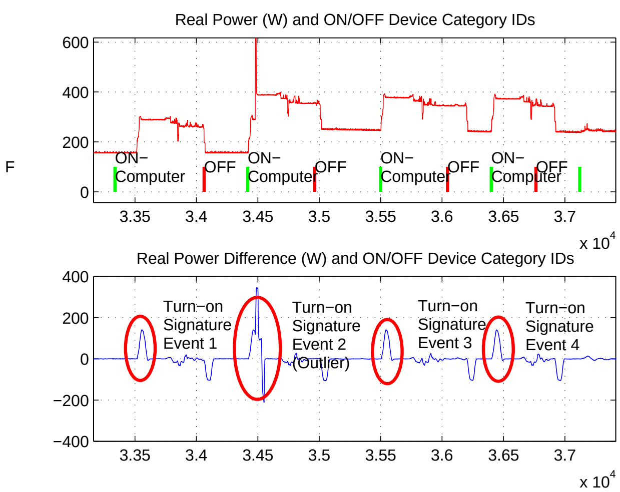

Fig. 6. Computer turn-on event outlier shown in the 2nd event.

load shapes), longer window size is used to detect event. For example, consider the dining room light and the laptop charger profile shown in Fig. 5. Both the appliances consumes about 38 Watts at event incidence. However, laptop charger then spends additional 38 Watts to fully turn on. Therefore, longer window lengths are used to detect laptop charger than in detecting 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. 6. 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.

distance domain is used to detect outliers

First, an event detector is used in the real power domain to estimate the exact switching time of the event. By in the training data. This is to account for the mismatches of the provided tagging info and the exact switching index.

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.

This section concentrates on extracting the feature windows in low frequency data. In particular the real and the reactive power differences are used to extract these windows. First, a separate event detector is used to correct the event detector is used in the Training Data to correct the mismatches

The procedures for calculating the real power and the reactive power include event detection, data smoothing, and power calculation.

IV. Validation-ML

Discuss cross validation here. this is the whole procedure for generating thresholds.

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. This is due to the fact that when multiple appliances are running, the absolute level cannot be used to detect whether one specific appliance is on or not. The change in real and reactive power consumption must be used to detect which appliance has turned on.

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.

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

Acknowledgment

The authors would like to thank...

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.