Non-intrusive Household Energy Consumption Disaggregation of Individual Appliances

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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. An 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 on 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 different load types and the approach to extracting signature windows for each appliance.

The goal of this paper is to document our approach and share insights and conclusions regarding household energy consumption disaggregation that we observed throughout the project.

II. Dataset and Methodology

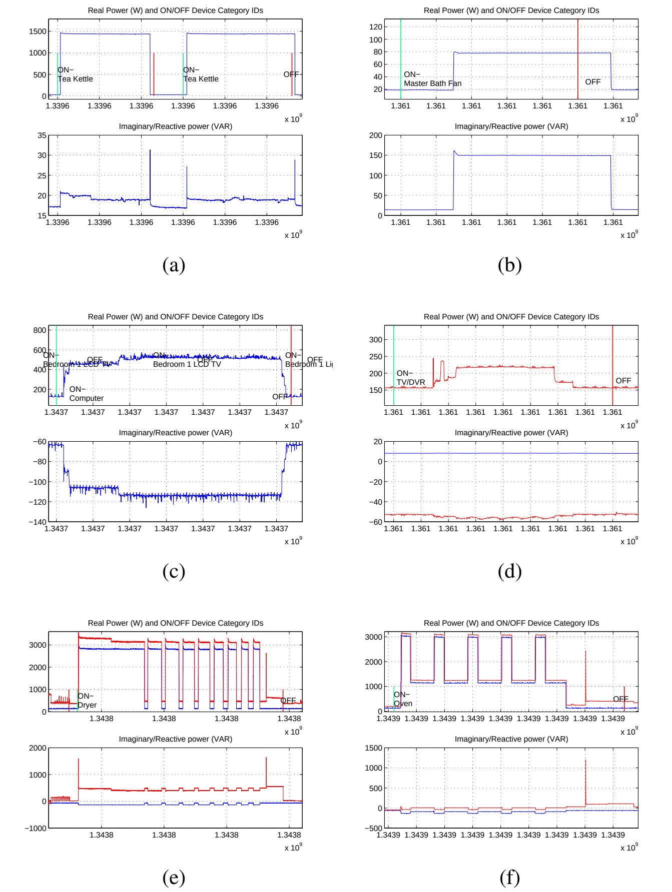
The dataset is publicly available on the competition website and contains voltage and current harmonics data for four households. The dataset also contains high frequency noise (EMI) data for each household, but is not required with our approach.

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

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



(a) (b)

(c) (d)

(e) (f)

Fig. 1. Load Types (a) Tea Kettle, (b) Master Bath Fan, (c) Computer, (d) TV, (e) Dryer, (f) Oven.

III. Training - Signature Window Extraction

This section concentrates on extracting the 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 its shape. The types include rectangular, non-rectangular, and cyclic loads.

1) Rectangular loads: These type of loads consumes constant power when operating. The load shapes are rectangular. They include resistive loads, such as lights, heaters, and kettle, and reactive loads such as fans. 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 characteristics when turning on. They include computers and TVs. These type of loads require longer window length than the rectangular loads.

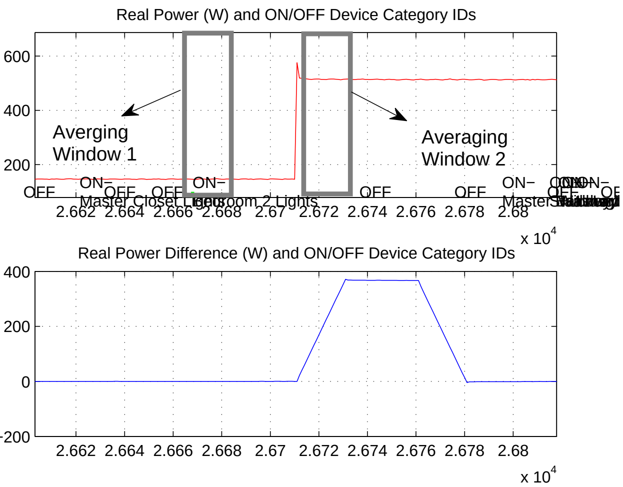


Fig. 2. Two Moving Average Windows.

3) Cyclical loads: - These type of loads change it's shape depending on the cycle of their operation. Dryer, oven, and washers are included in this category. Two approaches are suggested to detect these type of loads; using multiple windows or detecting a notable landmark during the operation.

B. Smoothed Power Differences

Now to train the windows, the real and the reactive power differences are calculated from two moving average windows. The smoothed difference $S(n)$ is defined as,

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

where N is the window size and D is the distance between the two windows. 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 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. 3, 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

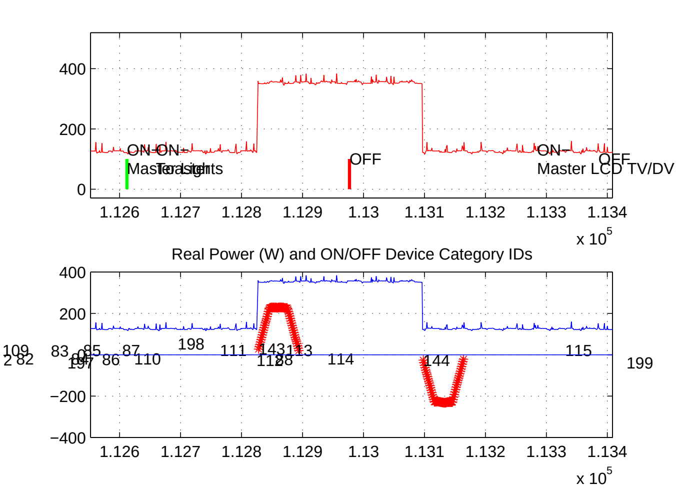


Fig. 3. Tagging Info Correction.

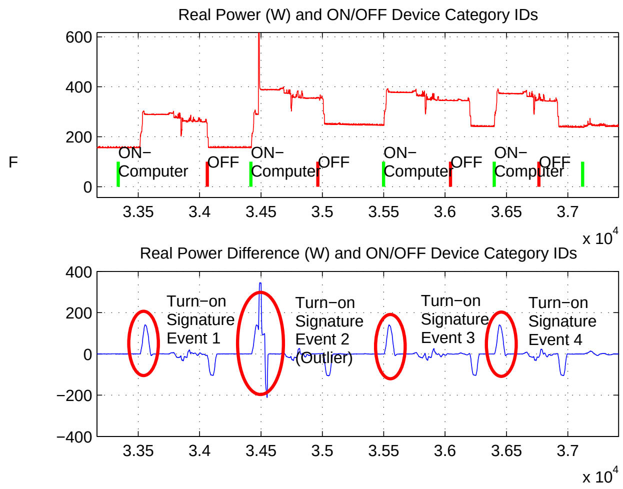


Fig. 5. Outlier.

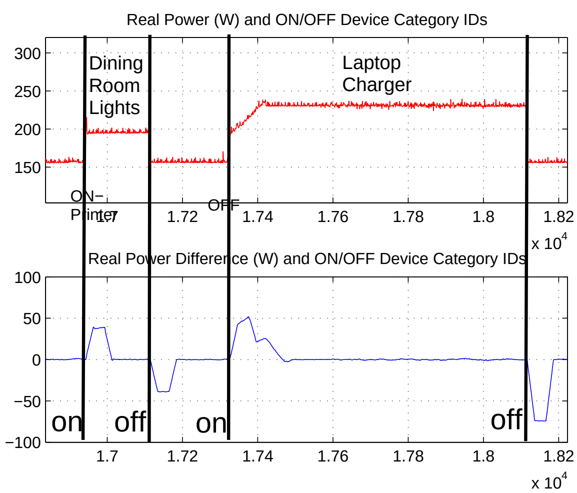


Fig. 4. Simple Distribution Feeder.

extracted starting from the corrected tagging info. If an appliance has an longer transient characteristics (non-rectangular 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. 4. 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. 5. 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 outliers and is not used in training the windows.

First a 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.

D. Load Types

-constant power - static - resistive (lights, heaters, kettle) - P domain and rectangular mainly - resistive + reactive (rotating like fans) - Q is a feature to help classify -dynamic - cyclical (washer dryer) - require rules, ie. landmark detection

1) Subsubsection Heading Here: Subsubsection text here.

IV. Cross-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.

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.