Disaggregation of Household Energy Consumption into 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 energy usage is typically monitored at single point by the utility, only providing information on the aggregate power consumption. In this paper, we attempt to disaggregate the energy usage data into specific appliances from single-point sensing measurements. Our method involves extracting events from the time-series data to obtain relevant features. We focus on two feature sets: low frequency and high frequency. For each set, we create an event detection algorithm for feature extraction. We present the results of our approach on a publicly available dataset.**

I. INTRODUCTION-ML

In this section, we provide the motivation and a brief description of the project. A short discussion of related work in this area, including the methodology of previous competition winners is also provided. This is followed by an overview of our approach, description of the raw data, and evaluation method.

A. approach/background

Our method focuses on real-time processing.

Show visualizations -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

-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
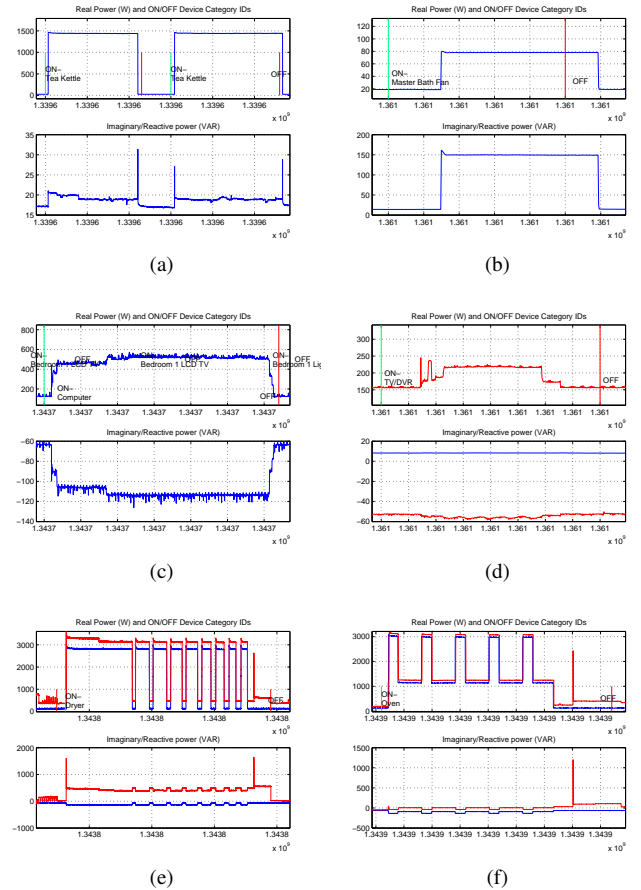

Fig. 1. Load Types (a) Tea Kettle, (b) Master Bath Fan, (c) Computer, (d) TV, (e) Dryer, (f) Oven.

II. 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.
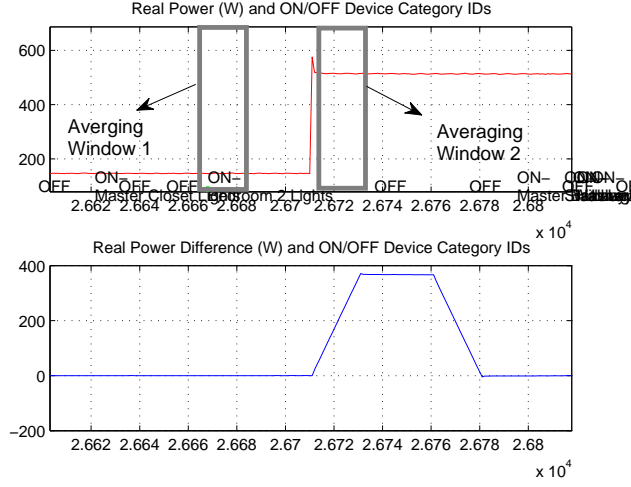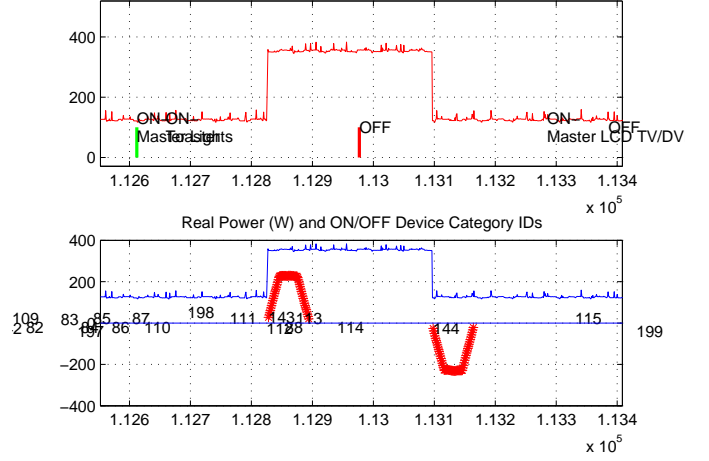
Fig. 2. Two Moving Average Windows.

Fig. 3. Tagging Info Correction.

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 characteristics when turning on. They include computers and TVs. These type of loads require longer window length than the rectangular loads.

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,

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

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 extracted starting from the corrected tagging info. If an appliance has an longer unique 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.
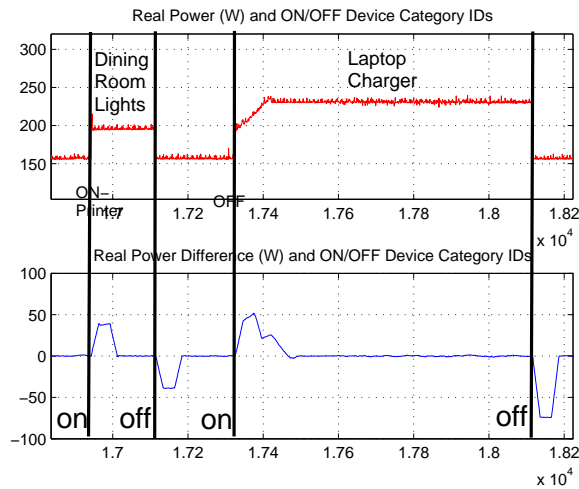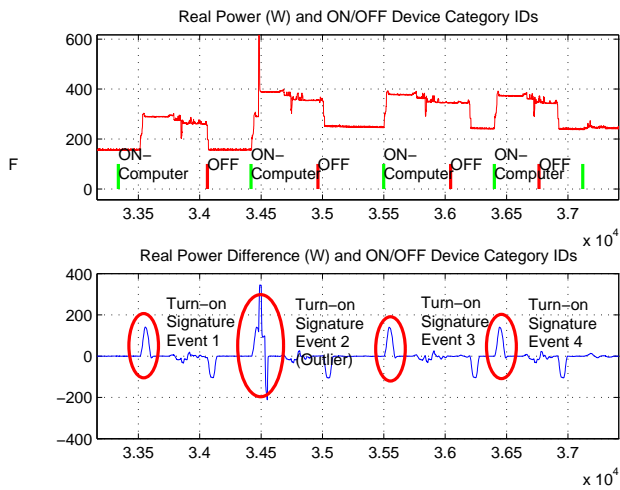
Fig. 4. Simple Distribution Feeder.

Fig. 5. Outlier.

1) Subsubsection Heading Here: Subsubsection text here.

III. CROSS-VALIDATION-ML

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

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

IV. TEST DATA

- rules for on/off pairing

V. 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.

REFERENCES

[1] H. Kopka and P. W. Daly, *A Guide to LaTeX*, 3rd ed. Harlow, England: Addison-Wesley, 1999.