Residential Load Classification from Single-Point Measurements Using Transient Signature Detection

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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 typically monitored at no more than a single point, only providing information on the aggregate power consumption. In this paper, we attempt to disaggregate energy usage data into specific major appliances using only single-point sensing measurements. Our method involves extracting turn-on and turn-off signature windows from real and reactive power time series data to obtain transient characteristics of each appliance. The proposed method focuses on using 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.**

***Index Terms*—Load disaggregation, load management, load signature, monitoring.**

I. Introduction

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

Prior research in the area of NILM has focused on the use of aggregate power consumption patterns to identify what appliance is being used and how much energy it is consuming. For example, [1] discusses various approaches in NILM, including detecting changes in steady-state power measurements and characterizing them as different events. Some challenges reported include different loads not exhibiting unique signatures in the 2-D feature space and the difficulty in determining steady-state features due to turn-on transient noise. The work recommended that advanced techniques should use 3rd order harmonics as a feature and use turn-on transients for event detection. The methodology in [2]–[8] follows a similar strategy. However, the classification can become challenging if the number of appliances in the home is large. Additionally, the signature of some appliances may change or vary over time due to operating conditions and the mode in which they are used.

In this paper, we present a simple 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 real and reactive power time series data. We focus on using the optimal window length for each appliance in order to capture unique signatures. We present the results of our approach using a publicly available dataset from [9]. The dataset and methodology are described in detail in Section II. Section III describes how signature windows are extracted for each appliance from the training data. Section IV then describes the cross-validation procedure using the training data and also application to the test data. Finally, Section V discusses results and topics for future work.

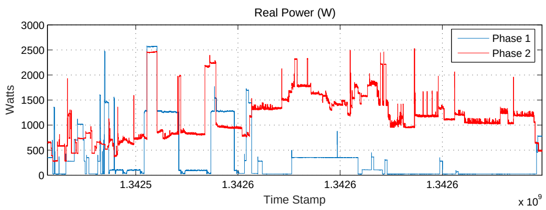
II. Transient Signature Window Approach

A. Methodology

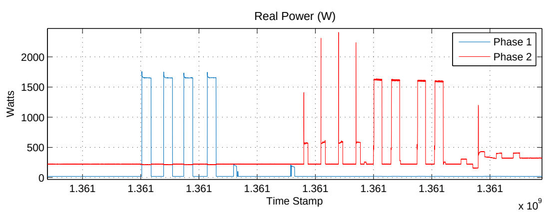
Typical aggregated load demand measured at the service entrance panel is shown Fig. 1 (a). It can be observed that multiple appliances are operating at any given time and it is not possible to determine which appliances are operating with reasonable certainty. The goal is to develop an interpretable yet effective classification approach, using measurements only at the service entrance panel, to detect which large appliance are turned on or off in a residence at any given time. When an appliance is turned on or off, a step change can be measured in real and reactive power consumption. By comparing the average power consumed before and after these transient events, we can calculate a time series representing the averaged difference in power consumption and facilitating discrimination among appliances. A flow chart of the proposed methodology is shown in Fig. 2.

The first step is to extract transient signature windows for each appliance. Raw data is converted from a power time series (P and Q) into an averaged power difference time series (ΔP_{avg} and ΔQ_{avg}) by taking the difference of two moving average windows. After ΔP_{avg} and ΔQ_{avg} are calculated, transient signature windows are extracted for each appliance. Each signature window, $w_{i,j}$ is of length $\mathrm{N}_{i,j}$, meaning each i^{th} appliance and corresponding j^{th} turn-on or turn-off event in the training data has a signature window with its own specified window length. This procedure is explained in more detail in Section III.

Once transient signatures are extracted for each appliance in the training data, cross-validation is performed. The objective of this step is to determine the ability of each signature window to only detect other events of the same appliance.



(a) Typical aggregated load demand measured at service entrance panel



(b) Dissagregated load data

Fig. 1. Example of (a) typical aggregated load data and (b) disaggregated load data. In each plot, real power consumption measured from the service entrance panel is shown for both phases.

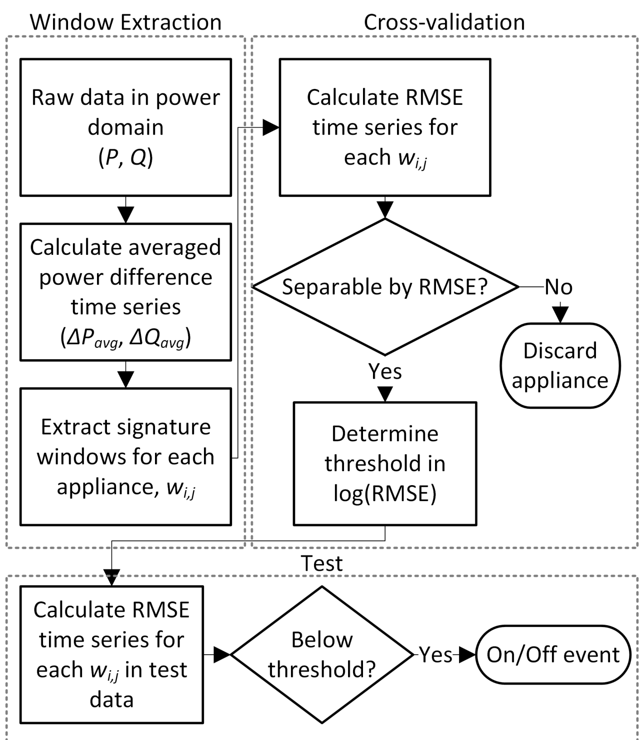


Fig. 2. Flow chart of proposed methodology. The procedure is separated into window extraction, cross-validation, and application to test data.

If an appliance can not be detected during cross-validation, it will not be predicted in the test set. For the test set, we use the cross-validated signature windows and threshold values to calculate an RMSE time series and detect appliance turn-on and turn-off events. The procedure is presented in Section IV. The results and conclusion are discussed in Section V.

B. Dataset

In this work, we utilize the full dataset available from [9], which is publicly available online and contains single-point sensing measurements from the service entrance panel for four households (labeled H1-H4). The measurements include the first five harmonics of rms voltage and current on two phases and high frequency noise (EMI) data for each household. It will be shown that the EMI data is not required with our approach (see further discussion in Section V). Although both training and test datasets are provided, only the training data provides labels and corresponding timestamps for each appliance.

Each training set consists of manually generated power consumption data for each appliance in each home. The training data is a time series 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, however, these are not always precise enough to correctly identify device turn-on and turn-off times. Correction of tagging labels for training data is therefore needed and 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.

III. Signature Window Extraction

This section describes how transient signature windows are extracted by using the averaged real and reactive power difference time series. In particular, a pair of turn-on and turn-off signature windows are trained for every event of each appliance in the training data.

A. Load Types

The appliances are first categorized into three load types based on their load shapes in P and Q. The types include instantaneous, delayed, and cyclical loads:

1) Instantaneous loads: These types of loads consume constant power during steady-state operation and their transient period is characterized by a sharp transition from zero to rated power consumption. Their load shapes are generally rectangular and consist primarily of resistive loads, such as incandescent lights and appliances with heating elements. Some inductive loads, such as small fans, also exhibit this load shape. A short duration signature window in the real and the reactive power difference time series is used to detect these loads. An example is shown in Fig. 3.

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

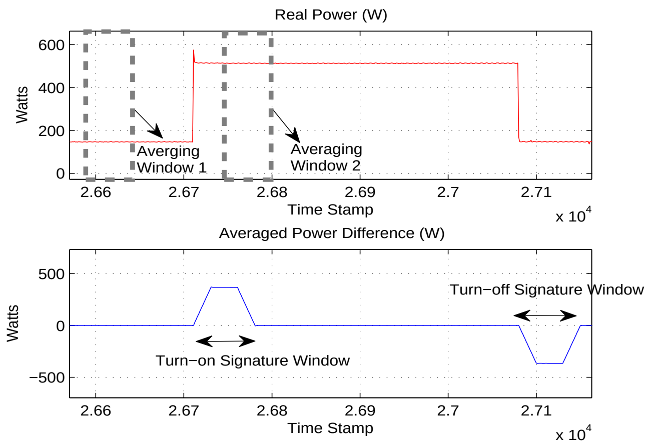


Fig. 3. Difference of two moving average windows to calculate averaged power difference time series. The bottom plot shows the transient signature for incandescent bedroom lights.

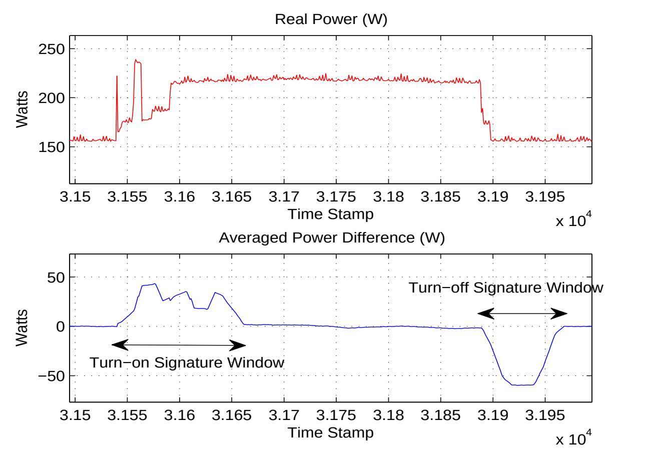


Fig. 4. Example of a delayed load shape (TV in Home 2) showing longer turn-on transient than instantaneous loads.

capture their unique transient shape. An example is shown in Fig. 4.

3) Cyclical loads: The amount of real or reactive power consumed by these loads change depending on the cycle of their operation. Dryers and ovens are included in this category. However, because they operate on preset cycles, there are only a few possible periodic load shapes they can follow. A modified approach is required to detect this type of load: identifying notable recurrent patterns during appliance operation.

B. Averaged Power Difference Time Series

Our approach relies on identifying appliance turn-on and turn-off events by detecting unique transient signatures in real and reactive power consumption. To extract transient signatures for each appliance, unique characteristics are observed in the averaged power difference time series. This calculation

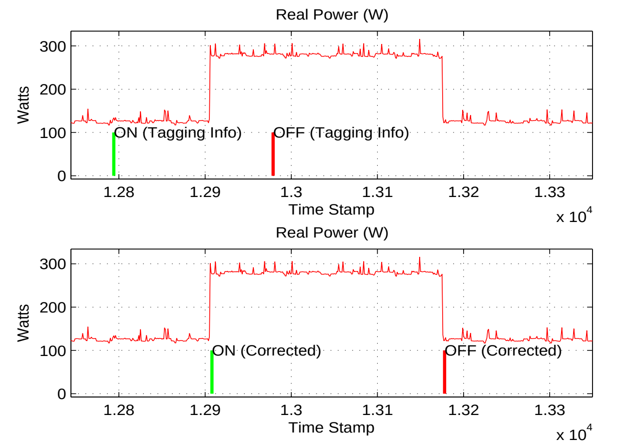


Fig. 5. Provided tagging labels are corrected in the averaged power difference time series.

is made from two moving average windows. The averaged difference for real power, $\Delta P_{avg}(n)$, is defined as,

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

where N is the window size and D is the distance between the two windows. The averaged difference for reactive power, $\Delta Q_{avg}(n)$, 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 averaged power difference time series to determine true appliance event indices, tagging labels from the raw data are first corrected. A threshold in the averaged real power difference is then set to indicate whether an event occurred, (i.e., an event occurred if $|\Delta P_{avg}(n)| >$ threshold). Then the corrected indices 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 bedroom lights do not align with the actual event incidence. The bottom plot shows when the first index of the averaged power difference is greater than the threshold; this index is used as the corrected tagging label. It should be noted that some appliances that consume very small real or reactive power are discarded as they can not be detected. For these appliances, using real and reactive power difference will cause false detections in the test data due to the effects of the noise. Additional features must be considered to detect such appliances.

C. Window Extraction

After calculating the averaged power difference time series, the next step is to extract the signatures for turn-on and turn-off events. For instantaneous load shapes, transient signature windows are extracted from the start of the turn-on event until the load reaches steady-state power consumption. If an appliance has longer transient characteristics (delayed load shape), a longer window size is used to capture the entire

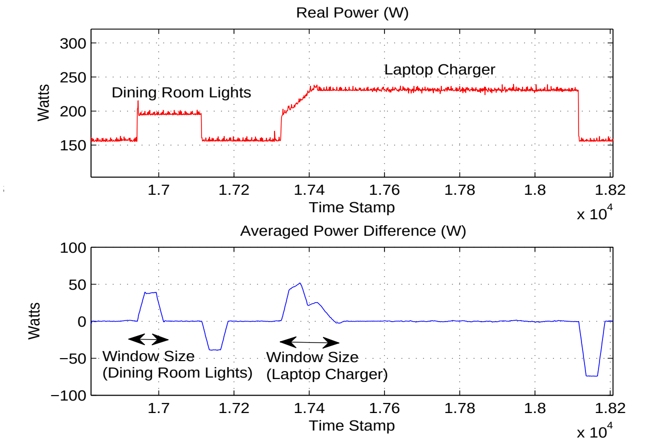


Fig. 6. Example of how choosing the appropriate window length can affect classification.

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 requires additional power to fully turn on. Therefore, if a longer window length is used, this characteristic is captured in the averaged power difference time series and can be used to discriminate it from other similar appliances. Thus, extracted signature windows define the unique transient characteristics in the averaged power difference time series for each event of each appliance in the training data. Table I provides the range for the lengths of extracted signature windows, categorized by load type.

Cyclical loads exhibit unique characteristics that are different from the instantaneous and the delayed loads. These types of appliances are difficult to be detected by using turn-on and turn-off signature windows because each step change in power consumption during the cycle can appear as individual appliances turning on or off. Therefore, for cyclical loads only, a window is trained to capture recurrent patterns during their operation. Consider the dryer in Home 2 as shown in Fig. 7. The load shape of the dryer has multiple sharp peaks during its operation. Therefore, a single window can be trained to detect these sharp peaks. In this case, the following rule can be made: “While the recurrent pattern window is detecting an event, the appliance is operating.”

Outlier detection is also held during this stage. Consider the four on/off events of a computer as shown in Fig. 8. It can be seen that when event two occurred, some background noise 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.

IV. Cross-Validation and Testing

In this section, we present the procedure for cross-validating the classification performance of the signature windows trained in Section III. The objective of cross-validation is to verify the ability of each signature window to detect other events of the

TABLE I
Range of Signature Window Lengths for Each Load Type

Load Type	Turn-on Window (Samples)	Turn-off Window (Samples)
Instantaneous	30 – 80	30 – 70
Delayed	40 – 300	40 – 150
Cyclical	70 – 200 (recurrent pattern)	

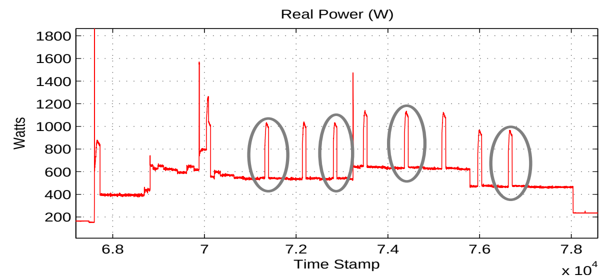


Fig. 7. Recurrent pattern during operation of the dryer in Home 2.

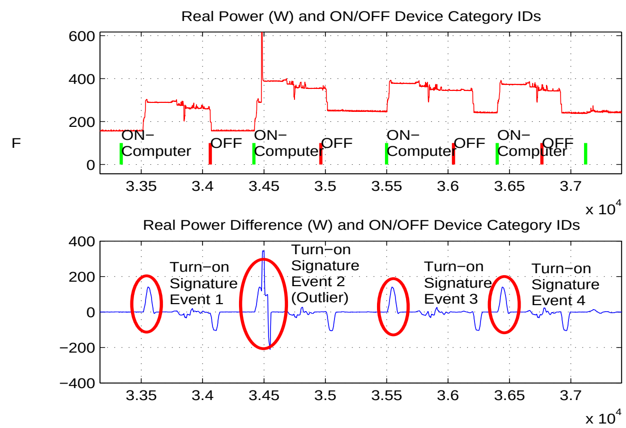


Fig. 8. Computer turn-on event outlier shown in the 2nd event.

same appliance in the training data. The root-mean-squared error (RMSE) is chosen as the metric to determine how well the signature window matches with the measured signal. The equations for calculating RMSE are shown in (2) and (3),

$$\mathrm{RMSE_P}(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(w_{i,j}(k) - \Delta P_{avg}(n+k))^2} \tag{2}$$

$$\mathrm{RMSE_Q}(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(w_{i,j}(k) - \Delta Q_{avg}(n+k))^2} \tag{3}$$

where $w_{i,j}$ is the transient signature window, with length $N = N_{i,j}$, for the j^{th} turn-on or turn-off event for appliance number i. Additionally, log(RMSE) is taken to improve separation of events.

An example for the cross-validation procedure is illustrated in Fig. 9 for the breadmaker. $\mathrm{RMSE_P}$ and $\mathrm{RMSE_Q}$ are calculated between the averaged power difference time series and the signature window for the appliance. Both $\mathrm{RMSE_P}$ and

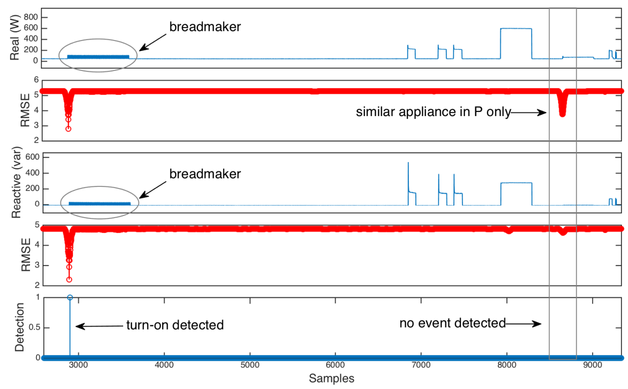


Fig. 9. Cross-validation of one training window for appliance "breadmaker". A turn-on event is detected when both RMSE time series simultaneously fall below the specified threshold.

TABLE II
NUMBER OF APPLIANCES VALIDATED AND DISCARDED FOR EACH HOME

Home No.	Total Appliances	Discarded	No. Validated (%)
H1	38	11	27 (71.1%)
H2	37	6	31 (83.8%)
H3	37	7	30 (81.1%)
H4	36	9	27 (75.0%)

RMSE_Q simultaneously reach a minimum when the extracted signature window closely matches the measured signal. This corresponds to the time when the associated appliance turns on or off in the averaged power difference time series. However, other appliances switching on and off cause RMSE_P and RMSE_Q value to vary and it is possible that both the RMSE values drop due to switching of an appliance with similar transient characteristics. This happens when the signature windows of the two appliances have a very similar shape and amplitude. To prevent this misclassification, RMSE thresholds (θ_P and θ_Q) are set to prevent other appliances from being detected. If such thresholds (θ_P and θ_Q) can not be set, the window is discarded. In this example, the window successfully detects the breadmaker turning-on with all the other events being rejected in the training set. The cross-validation results for all appliances are shown in Table II.

We then apply our algorithm to the provided test data and identify appliance operating intervals. The detections are made from the signature windows extracted from the training set with the threshold values acquired from cross-validation. The algorithm is shown below and is applied for every extracted signature window $w_{i,j}$.

Algorithm 1 Event Detection Algorithm

for every time instant n_0 **do**
  Calculate $\text{RMSE}_\text{P}(n_0)$ and $\text{RMSE}_\text{Q}(n_0)$
  if $\text{RMSE}_\text{P}(n_0) < \theta_P$ and $\text{RMSE}_\text{Q}(n_0) < \theta_Q$ **then**
    Event is detected at time instant n_0
  end if
end for

V. CONCLUSION

From our cross-validation and test results, the proposed strategy can be a simple yet effective method for disaggregation of household energy usage. One of the advantages of this approach is that it is more interpretable because it follows an intuitive approach 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 evident when compared to methods utilizing "black box" predictive models such as artificial neural networks. Furthermore, the proposed approach has the ability for real time processing. Because calculations are implemented as sliding windows, data can be streamed into the algorithm. Additionally, this method only utilized a subset of the entire dataset, needing only P and Q measurements. High frequency components could be used as features to help classify smaller appliances that were discarded during cross-validation. One of the primary drawbacks, however, is that manual identification of appropriate window lengths is required during training. Future work would consider automation of appropriate window lengths.

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