Home Appliance Detection from Aggregated Energy Consumption Data on a Single Circuit

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***Abstract*—Home appliance detection helps identify individual electrical and electronic appliances, which in turn can be used to foster more efficient energy usage habits and promote energy conservation, and enable load forecasting and demand response support. Prior approaches, however, require sub-metering high resolution power signals of individual appliances during training or testing, which is not practical as in practice such high resolution power signals would not be made available economically. We propose an alternative, low cost approach for home appliance detection that can be used to detect home appliances from the aggregated energy consumption data on a single circuit. In the first step, our proposed approach utilizes pattern matching algorithms to recover power from the minute level time series of aggregated energy use metered on a single circuit. In the second step, a domain knowledge based approach is proposed to label individual appliances based on matching with the known signatures for the appliances. Our proposed approach is validated using a dataset from Clarkson University's Smart Housing Project, where we apply the proposed approach to the dataset and measure precision and recall. The evaluation shows that our approach is promising in detecting those appliances that contribute the predominate energy consumption, such as mini-fridges, desktops, lamps, and laptops. We also analyze in detail the reasons why some appliances are harder to detect correctly.**

Keywords– Smart Housing, Smart Utilities, Appliance Detection, Energy Disaggregation, Feature Selection

I. Introduction

The rapid growth in energy consumption has raised the concern that it would cause some potential environmental consequences such as exhaustion of energy resources and climate change. In both Europe and the U.S., the residential sector, following transportation and industry, represents the third largest in energy consumption, contributing almost a quarter of the total energy used [5], [2]. Moreover, appliances, electronics, and lighting is ranked as the second largest group, contributing 34.6% of the residential energy usage [3]. Unfortunately, up to 39% of the energy used by the residential sector can be wasted [16].

To assist policy makers in understanding the energy saving opportunities, smart meters have been installed in residential homes and smart dorms to collect more electric energy consumption data. In particular, smart meter data collected in student apartments allows educators to monitor and detect heavy load appliances, educate students on the consequences of energy waste and emissions, and assist campus administrators to make policies in optimizing energy supply based on the collected data. Detecting individual appliances is important for enabling tasks such as providing feedback to consumers and promoting energy conservation habits, load forecasting, and demand response support.

Current home appliance detection approaches rely on modeling and detecting appliances from high resolution, sub-meter level data, which is not practical in some practice. In many realistic situations, such as energy consumption data from student dormitories, the aggregated energy signal is often the only data that we can collect economically. Therefore, it is highly desirable if it is feasible, to detect individual appliances based on the aggregated signals.

In this paper, we propose an approach to detecting home appliances from aggregated energy consumption data on a single circuit in student bedrooms. Our goal is modest and practical. Instead of reporting all possible appliances, we aim to detect a set of appliances that are commonly used in student dormitories [1]. As outlined in Figure 1, our approach consists of two major steps. First, to ease up detection, we apply pattern matching algorithms to transform the metered energy signals to power signals. Second, we identify segments of interest from the recovered power signals that are similar to known appliance power signatures. We then extract features and compare these features with the known signatures to infer appliances. To validate our approach, we apply it to a total of 25 circuits in 25 bedrooms in an apartment building at Clarkson University, measuring both precision and recall. The evaluation shows that our approach is promising in detecting a set of appliances that contribute a significant amount of energy used in a student bedroom. We also analyze in detail the reasons why certain appliances such as lamps and fans, are harder to detect correctly.

The rest of the paper is organized as follows. In Section II, we present a set of related work in appliance detection. Section III describes the proposed approach in detail, including the selected features and the feature extraction process as well as the decision making methodology. In Section IV, we provide an overview of Clarkson University's Smart Housing dataset that is used in our experiment, a summary of results, and an in-depth analysis of the performance of our approach. Finally, conclusion and potential direction for future research are described in Section V.

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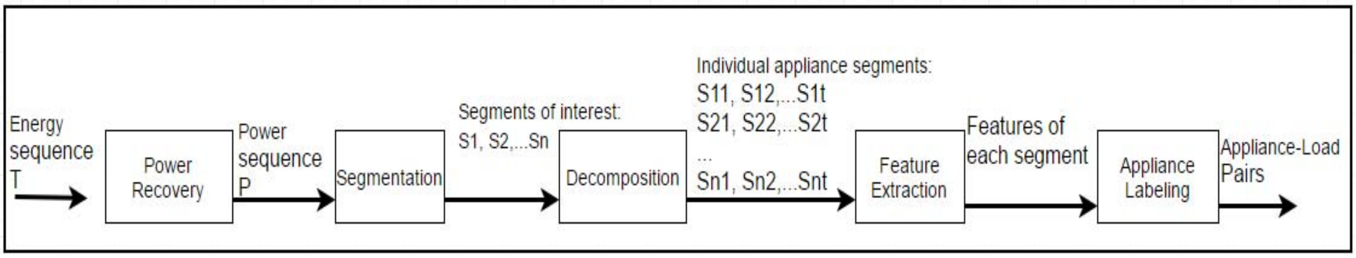


Figure 1: Workflow for the proposed appliance detection approach

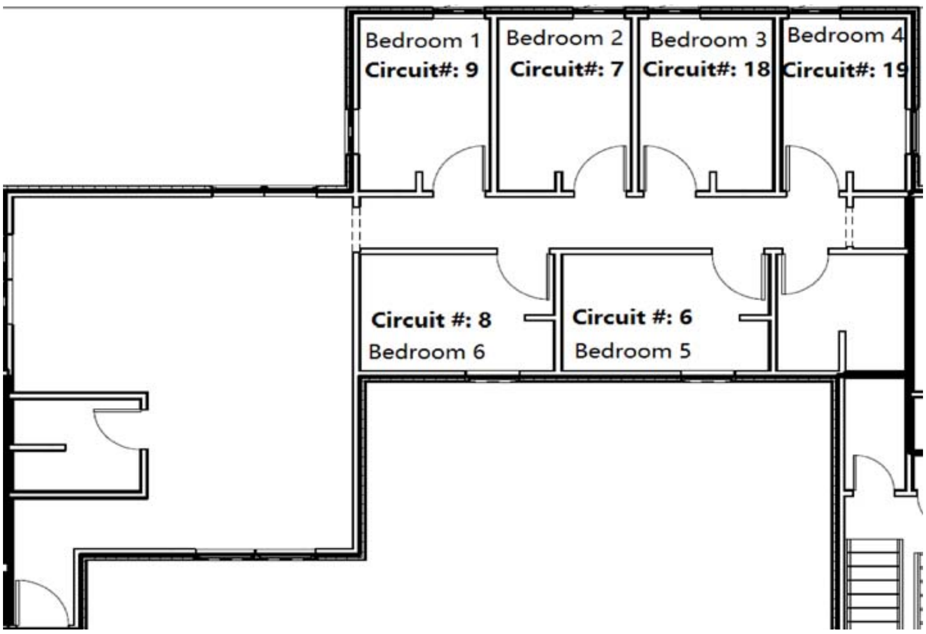


Figure 2: The layout of an apartment with 6 bedrooms each having a circuit providing electricity for all the loads in the room

II. Related Work

Smart meter based analysis of appliances is an active area of research. Guo, Wang, and Kashani's work is the closest related to ours [12]. It utilizes Hidden Markov Models and signal differencing to detect home appliances that have a strong state transition and duration signatures, such as refrigerators and washers, from aggregated power signals [12]. However, the authors report only results based on synthesized data and focus on only two kinds of appliances, refrigerators and washers.

Several other approaches have been proposed to analyze electrical home appliances, but they often have different purposes other than appliance detection, such as detection of appliance location and activity [13], recognition of concurrent ON/OFF switches [8], and mining correlation between appliance usage [11], [10], [9]. Ito et al. use the waveforms of current consumed by appliances to detect the model, location, and activity of conventional home appliances [13] for control purpose (e.g., to shut off an appliance when the room is vacant). In the learning stage, each appliance is plugged into an outlet for parameter learning. A user also needs to label this appliance with its model. Different from our approach, in the detecting stage, only one appliance is allowed to be plugged into an outlet at the same time. Chen et al. use high frequency current features and DTW (Dynamic Time Warping) technique to recognize when electronic appliances are switched on and off simultaneously [8]. Their focus is on detecting the moment when appliances are turned on. We use the aggregated energy series data to predict a set of possible appliances that are used on the same circuit.

Chen et al. develop a tool called CoPMiner (Correlation Pattern Miner) to capture the usage patterns and correlation among appliance usage [9]. The input of CoPMiner is a usage-interval database which contains the on/off time of each appliance. Instead, our work is to detect a set of appliances from the *aggregated* energy data. The output of our work would generate the appliance level usage interval data.

Energy disaggregation, a.k.a non-intrusive load monitoring (NILM), is the task of making inference about the different individual load of each appliance from an aggregate energy signal [14], [17]. Note that NILM assumes knowledge of individual appliances. Appliance detection could be applied to remove this assumption from NILM.

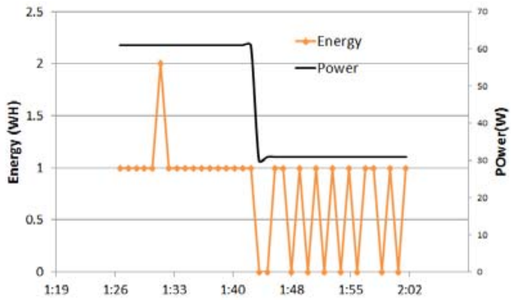


Figure 3: Metered energy (dotted) converted into power (solid)

III. Proposed Approach

This section describes the proposed approach for the appliance detection problem. Our approach consists of three phases: power recovery, identification and decomposition of relevant segments, feature extraction and appliance labeling.

A. Power Recovery

The power meters deployed at Clarkson record energy consumed in the previous minute in unit of WH. For example, the meters would generate a sequence of 010101.. for a 30W appliance, 01110111... for a 45W appliance, and 11111111... for a 60W appliance, and so on.

Since appliances are often characterized in terms of power, it is significantly easier for us to work with power signals rather than energy. Therefore, the first phase of our approach is to recover an aggregated power series from the observed energy series. To this end, we utilize the LCP algorithm (Longest Common Prefix) [15] to match segments of the energy time series with templates that are generated for a range of power up to 400W. In particular, to identify energy segments that are produced by power signals of 60W or higher, we customize LCP to recognize the longest common nonzero prefix (LCNP). Finally, our approach utilizes a threshold to determine whether an energy segment matched with a template can be transformed into the corresponding power series.

The detailed process is summarized in Algorithm 1. TP represents the set of templates we generate for a range of power, from 1 to 400W. Each template T in TP is a tuple $(p, c, L, nzero)$, where p is the power value, c is an initial remainder of power that lies in $(0, 59)$, L is a sequence of integers that specifies its energy consumption per minute, and $nzero$ specifies the number of nonzero integers in L. The combination of 400W and 60 possible power remainders yields a total of 24,000 different templates for TP.

To avoid the situation where a shorter template is matched despite a longer one exists, Algorithm 1 sorts the templates in descending order of $nzero$ (line 1). The algorithm then first identifies all segments that are 60W or above (the first while loop) before segments lower than 60W (the second while loop). The $threshold$ in our approach is set to 4. With the proposed approach, we can transform the aggregated energy time series data TS into an aggregated power time series data P. Figure 3 shows an example segment of energy time series (in WH) and the transformed power signal (in W). The dotted line is the raw energy sequence, and the solid line is the transformed power series. It is clear that power signals as shown by the solid line is much easier to interpret.

Algorithm 1 Power Recovery Algorithm

Input: TS, time series of energy use per minute (WH)
TP, energy templates for power up to 400W
Output: P, time series of power per minute (W)
1: Sort TP by $pt.nzero$ where $pt \in TP$ in descend order
2: $P[i] \leftarrow 0, Labeled[i] \leftarrow False\ i \in [1:n]$
// Longest Common Nonzero Prefix (for 60W and above)
3: **do**
4: $marked \leftarrow False$
5: **for** all unmarked segment S of TS **do**
6: **for** all template T of TP **do**
7: Find S, T that maximizes $n = LCNP(S, T.L)$
8: **if** $n \geq threshold$ **then**
9: $P[Pos : Pos + n - 1] \leftarrow T.power$
10: $Labeled[Pos : Pos + n - 1] \leftarrow True$
11: $marked \leftarrow True$
12: **while** $marked$
// Longest Common Prefix (for power below 60W)
13: **do**
14: $marked \leftarrow False$
15: **for** all unmarked segment S of TS **do**
16: **for** all template T of TP **do**
17: Find S, T that maximizes $n = LCP(S, T.L)$
18: $P[Pos : Pos + n - 1] \leftarrow T.power$
19: $Labeled[Pos : Pos + n - 1] \leftarrow True$
20: $marked \leftarrow True$
21: **while** $marked$

B. Signatures of Appliance Usage

After studying the usage data from our dataset, we observe three types of appliance signatures as well as two useful characteristics of appliance usage activities. These characteristics can be summarized as follows:

1) Periodical ON/OFF Appliances: Figure 4 shows a periodical ON/OFF pattern for a mini-fridge, which consumes 60 to 80W in the ON cycle and zero power in the OFF cycle.

2) Load Varying Appliances: Figure 5a shows the power usage from a desktop that consumes 120 to 210W power in active mode, 70W for 15 minutes in idle mode before dropping to the sleep mode that consumes 17W of power. The 120 to 210W power consumption is varying rather than constant. Therefore, we call it a load varying appliance. Figure 5b shows another segment of the same load varying desktop that is lifted by a constant 60W signal. Moreover, as shown in Figure 6, a laptop is also a varying load appliance. Note that both desktops and laptops exhibit behavior of stable state transitions.

3) Constant Power Appliances: Figures 7, 8, 13 show three examples of constant signals (or near constant) appearing at different bedrooms (a fan, a lamp, and an iPad charger).

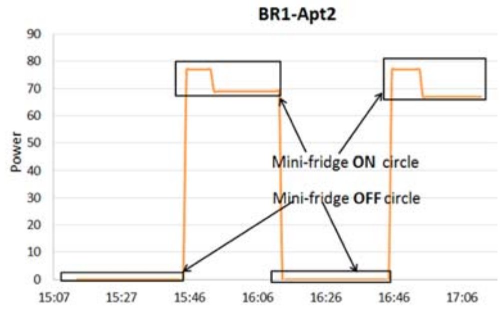
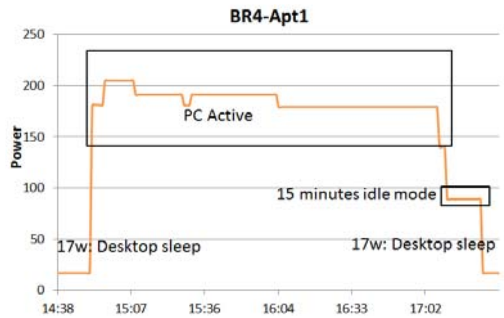
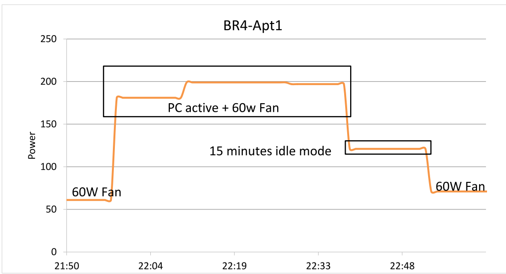


Figure 4: Power signal of a mini-fridge detected in BR1-Apt2 (Bedroom 1 of Apartment 2) on Dec. 31, 2016.



(a) Desktop in active, idle, and sleep mode (Dec. 3, 2016)



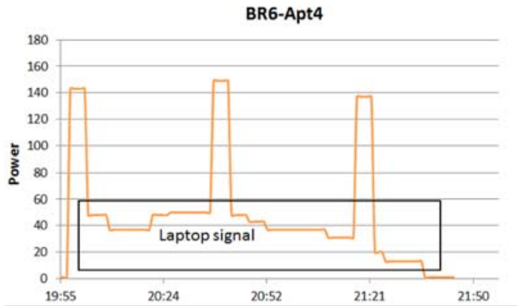
(b) Desktop lifted by constant 60W fan (Nov. 27, 2016)

Figure 5: Two power signal segments from same desktop

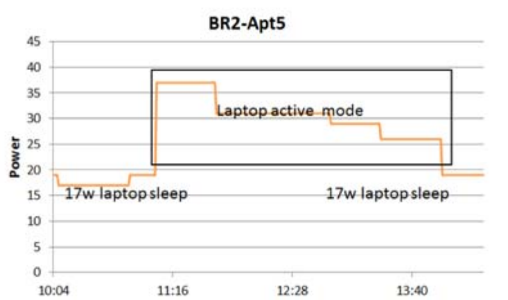
Note that in these examples, the surrounding signals are zero, which helps confirm that the constant signals are from a single appliance. Moreover, the base signal shown in Figure 9 is also constant (a humidifier).

4) Concurrent Appliance Usage: Multiple appliances may be used at the same time. Figure 6a shows an example of concurrent appliance usage where a laptop and a mini-fridge are used at the same time.

5) Time Dependent: The usage of appliances can also be time dependent, which can help disambiguate. For example, it is more likely for a student to use a desktop for gaming between 7 PM to 1 AM, a constant power appliance that is below 100W and used between 11 AM to 2 PM is more likely to be a fan rather than a lamp, and a load-varyng appliance that is used between 2 PM to 10 PM is more likely to be a laptop.



(a) Mini-fridge lifted by laptop (Nov. 27, 2016)



(b) Laptop in active and sleep modes (Dec. 2, 2016)

Figure 6: Power signals of two detected laptops

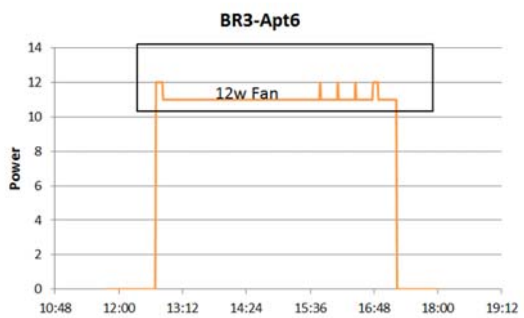


Figure 7: A fan (Nov. 29, 2016)

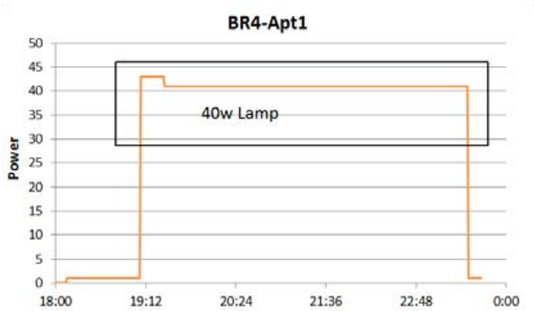


Figure 8: A lamp (Nov. 2, 2016)

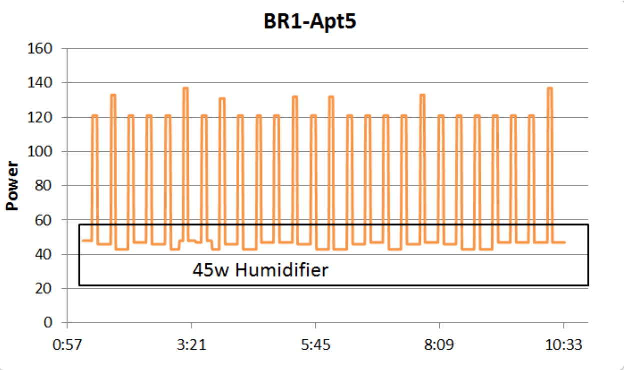


Figure 9: A humidifier (Dec. 2, 2016)

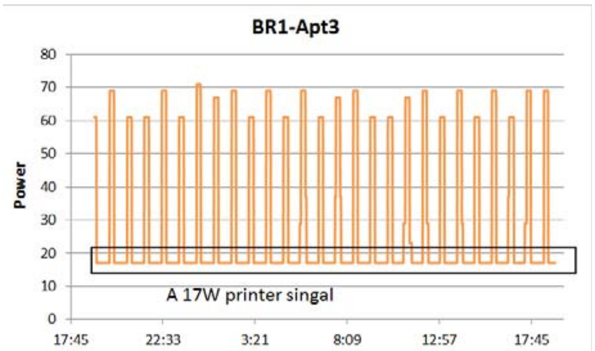


Figure 10: A printer (Nov. 25, 2016)

C. Segment Identification and Decomposition

In this phase, we identify segments of the aggregated power signal that match the signatures and usage patterns presented in Section III-B. We adopt the following process. First, we detect the periodical signal with a clear ON/OFF cyclic pattern. Once detected, the mini-fridge signal will be subtracted from the aggregated power signal to enable further detection. Second, we detect constant power appliances such as printers, lamps, fans, and humidifiers. Third, we detect load varying appliances such as desktops and laptops. In the process, we also remove the heavy load appliances such as a hair dryer, which looks like an outlier in our data due to its high power and short periods of use (a few minutes).

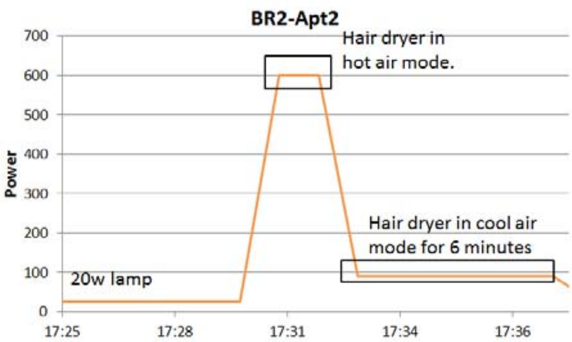


Figure 11: A hair dryer (Nov. 29, 2016)

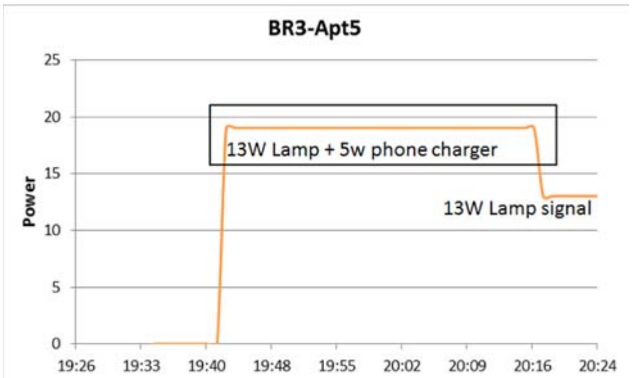


Figure 12: A phone charger (Nov. 26, 2016)

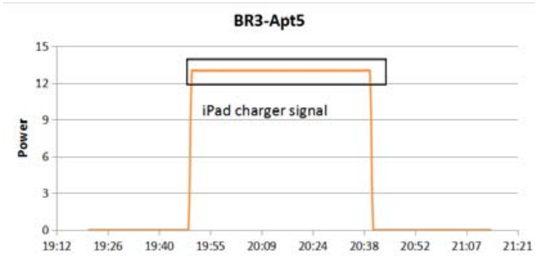


Figure 13: An iPad charger (Nov. 24, 2016)

Since multiple appliances can be turned on at the same time, the power signal of one appliance could be "lifted" by that of another. Therefore, we also attempt to decompose such aggregated segments into individual components that represent a single appliance. This could be helped if the component appliances can be first detected when they are used alone. It is worthwhile to note that our approach would not be able to separate apart two load varying appliances that are used at the same time. However, this would not a major problem in practice since major appliances such as a laptop and a desktop would rarely be used at the same time in a student bedroom.

D. Feature Extraction and Appliance Labeling

Once we obtain a segment of signal that represents an appliance, we extract the following features from it: power, duration, hour of day, and whether the power is constant or not. Table I depicts characteristics of common appliances compiled from published data [7], [6], [4]. To infer the appliance, we compare the extracted features with the common appliances shown in Table I. In our inference, we also apply common sense knowledge such as the time and duration when an appliance is more likely to be used than others.

Table II shows examples of ten types of appliances that are detected using our approach, along with the reasons for inferring each of these appliances from the recovered power signals. For example, our approach infers a desktop by checking the duration of the idle state and the power consumption

Table I: Reference power statistics for appliances

Appliances	**Min (w)**	**Avg (w)**	**Max (w)**	**Constant**
Mini-fridge	60	N/A	112	No
Desktop	60	100	300	No
Desktop Idle	43	N/A	114	Yes
Laptop	20	60	100	No
Fan	10	15	100	Yes
Incandescent Lamp	40	N/A	150	Yes
CFL Lamp	8	N/A	55	Yes
LED Lamp	6	N/A	28	Yes
Humidifier	18	25	81	Yes
Printer OFF	1.6	0	4.5	Yes
Printer ON	1.7	131	481.9	Yes
Hair Dryer (hot air)	800	1500	1800	Yes
Hair Dryer (cool)	N/A	70	N/A	Yes
Phone Charger	0.27	4	7.5	Yes
Ipad Charger	10	10	12	Yes
Projector	85	N/A	350	Yes
Amplifier	21	34	70	Yes

Table II: Sample appliances inferred from signal characteristics

Figure	**Inferred Appliances**	**Reasoning**
Fig 4	Mini-fridge	Periodical ON/OFF pattern (60 to $80w$ for ON state, and 0w for OFF state)
Fig 5a, Fig 5b	Desktop	Varying power between 110W and 150W, 14:30 to 17:30, 21:10 to 23:00, 15 minutes idle
Fig 6a, Fig 6b	Laptop	Varying between 15W and 50W, 20:00 to 21:30, 11:00 to 13:30
Fig 7	Fan	Constant of 12W, 5 hours, 12:30 to 17:00.
Fig 8	Lamp	Constant of 20W, 17 minutes, 9:58 to 10:15
Fig 9	Humidifier	Constant of 25W, whole night.
Fig 10	Printer (standby)	Constant of 17W, 5 days.
Fig 11	Hair Dryer	Constant 600W, 2 minutes, 90w for 6 minutes
Fig 12	Phone charger	Constant 5W, 35 minutes.
Fig 13	Ipad charger	Constant 12W, 50 minutes

in each mode, a laptop by hour of use and power range, a mini-fridge by the periodicity and power range, and finally, a lamp or fan, by requiring the presence of constant loads, and a cerain hour and duration of use.

E. Evaluation Metrics

For each kind of appliance, the performance of our detection approach is evaluated by calculating the recall and precision, which are defined as follows:

$$\text{Recall} = \frac{\#\text{Correctly detected appliances}}{\#\text{ Appliances found in on-site visit}} \tag{1}$$

$$\text{Precision} = \frac{\#\text{ Correctly detected appliances}}{\#\text{ Appliances inferred}} \tag{2}$$

IV. Experiments and Results

A. The Clarkson Smart Housing Dataset

We use a subset of Clarkson University's Smart Housing data to evaluate our approach. Our dataset contains 28 bedrooms from the 6 apartments in a residential building. Two of these apartments have 6 bedrooms each and four apartments contain 4 bedrooms each. Students within the same apartment share the living room and kitchen area, and bathrooms. Three out of the 28 bedrooms are vacant during Fall 2016. Therefore, we have data from a total of 25 bedrooms to work with.

Electricity usage is monitored in each apartment via smart meters installed at the kitchen range, bathroom outlet, living room outlet, television outlet, bedroom outlets, kitchen outlets, bathroom lights, and common area lights. There are 10 outlets within each bedroom that are connected to the same circuit.

Water usage is monitored using 7 smart meters installed at the kitchen sink (hot and cold), bathroom sink (hot and cold), shower (hot and cold) and toilet (cold only). Environmental data is monitored by smart meters by monitoring indoor temperature, humidity, and dew point. Water and electricity usage, environmental data from each smart meter is sampled every minute and transmitted via Ethernet to a central server. The central server also provides capabilities for decision makers to visualize, analyze and retrieve usage data for a specific time period. Finally, each apartment is equipped with an eco-feedback display that provides feedback to the tenants to encourage conservation behaviors.

Each bedroom accommodates at most one student. There are 10 electricity sockets in each bedroom that connect to a single circuit. This circuit is metered to monitor the minute level, aggregated electricity usage data in Watt-Hour unit, which provides the data for this research.

We process 10 days of data from the 25 bedrooms in the 6 apartments, from Nov. 25, 2016, to Dec. 4, 2016. We assume that most of the appliances will be used during this time frame. Note that we include two days from the Thanksgiving break (Nov. 25 and 26) to ease the detection of appliances such as a mini-fridge, which is most likely to remain plugged in when the owner leaves the bedroom.

B. Experiment Setup

Following our approach outlined in Section III, we manually process the data from Nov. 25 to Dec. 4, 2016 for the 25 bedrooms. To assist appliance labeling, the power statistics in Table I is used as reference, which is compiled from the published sources [7], [6], [4]. To validate our inference, we conducted an onsite visit on Mar. 9, 2017 during the Spring break to collect ground truth. Note that our ground truth is considered partial as students take away mobile appliances such as laptops and iPhone during the break.

Table III summarizes the appliances that are detected. Overall, the values of precision and recall for common appliances such as mini-fridges, desktops, laptops, and lamps are reasonably high, indicating that our approach is promising.

C. Errors in Mini-fridge Detection

As shown in Table III, there are two false positives for mini-fridges. One possible explanation is that the students might have moved their mini-fridges from the bedrooms to the common living room before our visit. The false negative may be caused because the bedroom might have acquired a new mini-fridge between Dec. 4, 2016 and our onsite vist on Mar. 9, 2017.

Table III: Appliances detected from 25 bedrooms.

Appliance Name	Total Detected	Partial Ground Truth	Recall	Precision
Major Energy Consumption Appliances				
Mini-fridge	12	11	**10/11**	**10/12**
Desktop	7	5	**5/5**	**5/7**
Lamp	17	15	**14/15**	**14/15**
Fan	13	15	9/15	9/13
Uncommon Appliances				
Humidifier	6	1	1/1	1/6
Printer	1	2	0/2	0/1
Hair Dryer	3	1	N/A	N/A
Carry-on Appliances				
Laptop	15	5	**4/5**	4/15
Phone charger	9	0	N/A	N/A
Ipad charger	7	1	N/A	N/A

D. Errors in Desktop Detection

We mistakenly report two bedrooms as having a desktop. During our visit, we observed only one monitor, but no desktop in these two rooms, indicating that there may be a laptop in each bedroom instead, but which may have been taken away during the Spring break.

Figure 14 depicts the two segments that are mislabeled as desktops. The constant 147W signal in Figure 14a is actually from a projector, which is not in the list of appliances that we consider. Had we considered the projector, the segment in Figure 14a would have been correctly labeled as a laptop.

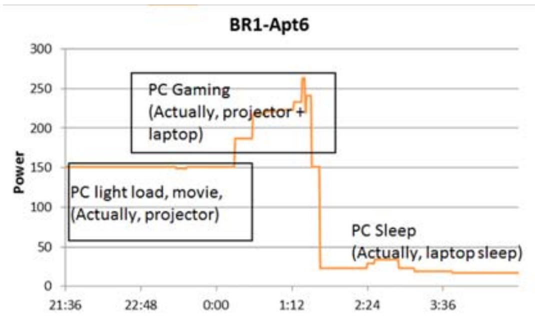
The segment of 137 to 247W in Figure 14b is mistakenly decomposed into a 55w mini-fridge component plus a PC. The constant 70W segment was mistakenly labeled as the desktop idle mode based on the assumption that the desktop was set to "never turn to sleep" mode. However, by looking at more data for this bedroom, we are able to detect a constant 70W signal that lasts for the whole night on Nov. 4, 2016, leading to the conclusion that the 70W is actually from a fan. Had we processed the data on Nov. 4, 2016, in advance, the mislabeled segment on Dec. 2, 2016, would have been correctly labeled as a laptop.

E. Errors in Laptop Detection

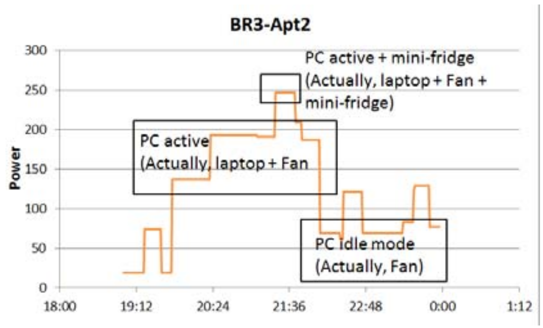
Four out of 5 bedrooms are correctly predicted as hosting a laptop, but there is one false negative bedroom. By looking at more data for that bedroom, we are able to detect a laptop signal on Nov. 2, 2016, as shown in Figure 15, This indicates that our approach could correct false negatives by processing more data from the beginning to catch a time when an appliance is used. On the other hand, the false positive laptops may be due to the fact that students take away their laptops during the Spring break when we conducted our on-site visit to their bedrooms.

F. Errors in Fan Detection

We detected 13 fans from our dataset, and we observed 15 during our onsite visit. 9 out of the 13 fans are inferred correctly. The 6 false negatives can be classified into three types of reasons: three fans are mislabeled as a desktop in



(a) A false positive for desktop (Nov. 29, 2016)



(b) A false positive for desktop (Dec. 1, 2016)

Figure 14: Two false positives for desktop

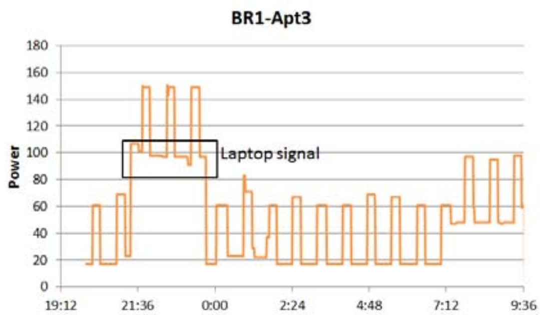


Figure 15: A laptop missed on one day but detected on a different day (Nov 2, 2016)

idle mode; one is mislabeled as a humidifier; two 15W small fans are mislabeled as a laptop in sleep mode.

The 4 false positives can be classified into two types: two lamps were mislabeled as fans; two laptops in sleep mode were mislabeled as fans.

G. Errors in Lamp Detection

We detected 17 lamps from our dataset, and observed 15 during onsite visit. 14 of the 17 lamps are inferred correctly. The one false negative is created because we mislabel the lamp to a humidifier.

The 3 false positives can be classified into two types: two fans are mislabeled to lamps; one amplifier is mislabeled as a lamp.

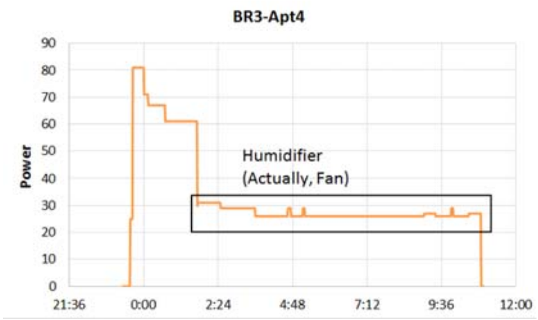


Figure 16: A 30W fan mislabeled as a humidifier

promising in detecting appliances witch contribute a significant power consumption in a student dormitory environment.

The current work is done manually. Based on the promising result we report here, our logical next step is to create algorithms to automate this process. Furthermore, a more comprehensive survey should be conducted in order to get better ground truth data. Another important direction is to incorporate more features to improve the detection accuracy, such as temperature, humidity, and water usage. For example, a fan would be more likely to be used when the indoor temperature is high, the indoor humidity would increase after using a humidifier for a while, and students may use a hair dryer after taking a shower.

H. Detection of Uncommon Appliances

Humidifiers, printers, and hair dryers are uncommon appliances in our experiment. In our current decision making process, a humidifier will be reported if we detect a constant signal that appears for a whole night. Moreover, to avoid confusing a printer with computers in sleep mode, we will label a printer only if a constant base signal appears for more than 3 days. Lastly, a hair dryer will be reported if a 1000 to 1500w segment that lasts shorter than 5 minutes is detected.

As shown in Figure 16, a fan or a lamp can be mislabeled as a humidifier. Also, these uncommon appliances may be placed in a hidden area that is invisible to us, thus creating false positives.

I. Carry-on Appliances

It is highly likely that students take away with them such mobile appliances as phone chargers, iPad chargers, and laptops during the Spring break.

J. Discussion

Overall, as shown in Table III, our approach is promising in detecting high power appliances such as mini-fridges, desktops, lamps, and laptops.

Low power appliances, such as a phone charger (5W), iPad charger (10W), cannot be detected in a bedroom when a desktop is turned on. However, our approach could discover these appliances if they are used in a period when the desktop is turned off. In general, more appliances can be detected and fewer false positives for each appliance could be achieved by checking more data.

Our current research is done manually, so we are limited in this regard. For the poor recall values for uncommon and carry-on appliances, the ground truth data may contain some errors. These factors should be considered when reading Table III, and the recall may not be as bad as they look on the surface.

V. Conclusion and Future Work

In this paper, we propose an unsupervised appliance detection approach based on analysis of aggregated energy usage data on a single circuit. We select an initial feature set that is easy to obtain. The evaluation result shows that our approach is

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