Load-Disaggregation for Increased Coverage in a Building Energy Auditing Network

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***Abstract*—Buildings in the United States currently consume approximately 72% of electricity in the United States [1], and 30% of that energy consumed is wasted [2]. With the specter of global warming it is of paramount importance that building energy consumption be reduced and optimized. In this work, we study the data gathered from a set of wireless and wired sensors to disaggregate the power usage of energy consumers within a building. In order to obtain more fine-grained view of the energy consumption, we decompose the data spatio-temporally by individual appliance and across appliances such as laptops, desktops, and monitors. We identify the various components and behaviors within and across individual appliances and apply various techniques, such as non-intrusive load monitoring, to infer who is consuming what, where, and how much is consumed. Such inferences allow us to reduce the cost of deployment, while also identifying optimization and reduction opportunities for buildings energy consumption. We employed the power consumption of appliances to determine operating states using an Allan Variance-based algorithm. The appliances states and power level were stored in a library used by and algorithm that calculates possible combination of states given a certain trace.**

I. INTRODUCTION

The ubiquity of technology in almost every aspect of our life has led to an increase in energy consumption during the last two decades. In United States, 72% of the electricity is consumed in buildings [1] and even more impressive is that 30% of the energy is wasted[2]. In order to make a more efficient use of energy and make right decisions about the implementation of energy conservation policies in buildings, it is important to know where, when and by whom the energy is being utilized. Even though it may seems the right choice to attach a sensor to each appliance, it is hard to deploy and furthermore, it is not a cost-effective option due to the great amount of electrical devices that may exist within a building. But given the tree-shaped arrangement of an electric system allows to place sensors in strategic locations and using disaggregation techniques, determine where, how and by whom the energy is being consumed. The purpose of this paper is to present an approach to disaggregate the energy consumption relying in the subset-sum algorithm and by a probabilistic state machine for each appliance class, in order to infer which appliances and their states of operation at a given time. Our approach is based in the additivity principle presented in [3]. We will utilized the data collected by a wireless sensor network deployed in a typical computer science department building [3 to understand the energy consumption of different appliances such as laptops, desktops, and monitors. We will use the principle of non-intrusive load monitoring to infer which appliances are consuming energy and the operating states of these appliances. The goal of our research is being able to infer which appliances and their states in a given moment, by knowing the aggregate power at a certain location in the building. Among the biggest challenges are the great amount of states that a specific appliance could operate, and the overlapping of power consumption level between different appliances, and the unknown power consumption behavior of internal components within some appliances as laptops. In the next section we will present related work and improvements to non-intrusive load monitoring in environments that differs from buildings because of the types of appliances evaluated. In Section 3 we will explain our different approaches for states identification, the process of building a states library, the use of a subset sum approach to obtain combinations of states that can be present in an aggregate trace, and we will introduce the approach of using a probabilistic state machine of transitions. Section 4 will contain results of our states identification algorithm and the obtained library of states. In Section 5, we will give discuss some conclusions and future work recommendations related to this project.

II. RELATED WORK

It has been shown that the amount of energy consumption of homes and offices can be reduced up to 20% if detailed energy consumption is available[4]. However, this is not the scenario in buildings, where the energy consumption information is an aggregate of all the devices within, and is known in a monthly basis. Some of the approaches previously proposed to increase the availability and amount of energy usage information are based on placing a sensing instrument at the main feed. This is the case in the patented work presented by Hart [5]. He developed a method for individual electrical loads from a residential building using real an reactive power measurements. This approach was improved by Norford and Leeb [6] with the introduction of transient event detection. A more recent approach was the one proposed by Laughman et. al. [7], who describe the use of current harmonics as another parameter for disaggregation. On the other hand, there are approaches that aims to improve the amount of information about the energy consumption of specific devices by developing power meters and wireless based energy monitoring systems[8]-

[10]. However, this is not a good approach for a building environment due to the cost of deployment and maintenance. The AC meter (ACME) utilized to gather data for this work, is described in [11], and the deployment of a wireless sensor network using these devices is presented in [12].

III. Methodology

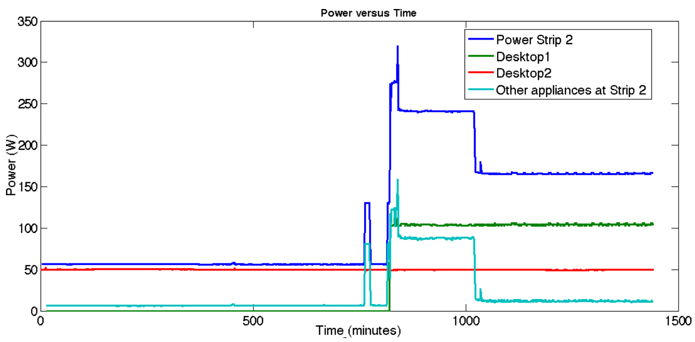

Fig. 1. The graph shows the additivity principle in a power strip that has two desktops. Knowing the aggregated power consumption at the power strip, and two desktops, we can obtain the other appliances trace by subtracting the power consumed by the two desktops from the power strip total power.

We use the power consumption of appliances different states as our feature of interest, taking advantage of the additive feature in the energy distribution arrangement of a building. The principle of additivity can be observed in Fig. 1. The graph shows the aggregate power consumption in a power strip, two desktops, and the obtained power trace of other appliances by subtracting the power consumption of the two desktop to the total power at the power strip. The additivity principle that building energy arrangement possess is explained in [3]. Furthermore, we will focus on state changes and transitions as the events used for non-intrusive load monitoring. The first step was to change the sampling rate of the AC Meter from 1 reading per minute to 1 reading per second to have a better insight about the transitions. Subsequently, we decided to collect new traces in order to have an idea of what were the conditions for a given power consumption level. For example, we varied an LCD brightness and contrast levels, while taking power level measurements. Then, when we looked at the power trace, we would have an idea of why a transition or state change occurred at a specific moment. Throughout this section we will describe three different approaches to identify signatures and state changes on individual appliances power traces Then we explain how we built our library of states. The library will be used to find possible combination of states that sum up to the power consumption of a certain state in an aggregate trace. In order to have another discriminatory parameter,, each appliances will have a transition vector. After identifying the transitions of each appliance, we will calculate the probability of changing from a certain state X to another state Y. This will be known as probabilistic state machine throughout the rest of this paper.

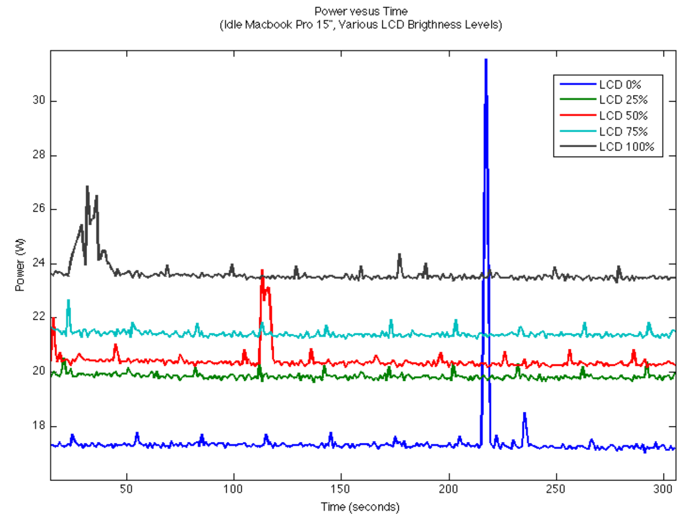

Fig. 2. This graphs shows 5 different power consumption levels of an idle MacBook Pro. Each trace was taken with a different LCD brightness level.

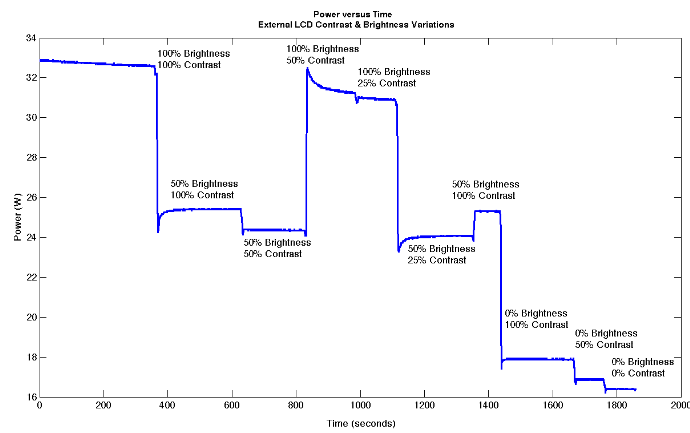

Fig. 3. An external LCD with different brightness and contrast levels and their associated power consumption. The power consumption varies from 17 W to 33 W. The changes in power consumption are greater when the brightness is changed.

A. Appliance Signatures

An appliance signature is a set of information that help to distinguish one appliance from any other. The set of parameters can include power consumption, power factor, transitions, current transient behavior, etc. Our approach will utilize the power consumption of appliances at different states, transitions, and the probability of a transition to occur as the distinguishing parameters between appliances. Examples of appliances signatures for a MacBook Pro with different LCD levels, and the variation in power consumption of an external LCD with respect to the brightness and contrast levels are presented in Fig. 2 and Fig. 3 respectively.

B. State Identification Algorithms

1) First algorithm: The approach of the first algorithm to identify state changes was very simple, considering the difference in power consumption between two consecutive points and comparing it with twice the standard deviation of all the changes between a each pair of consecutive points . A disadvantage of this algorithm was sensitivity to reading errors, mainly peaks. The next approach relies on more points for state changes identification.

```
stateChange1(A)
 for i=1 to size(A)-1
        changes[i]=|A(i)-A(i+1)|
std=standardDeviation(changes)
for j=1 to size(changes)
        if(changes(j)>=2*std)
                state change at A(j+1)
```

2) Second Algorithm: In contrast to the first algorithm, in this case, we considered four points to detect state changes. The idea of this algorithm is that given a certain point considered the previous two, if there is a change greater than two times the standard deviation of the changes between adjacent points, let's call it *compVal*, and the changes of the subsequent two points were smaller than *compVal*, then it was considered a state change. The result was less sensitivity to peaks in comparison with the first approach, but there was still the question if two points behind and two points ahead was the appropiate window size, why not three, or five. The next algorithm will be able to identify the right window size.

```
stateChange2(A)
BEGIN
 for i=1 to size(A)-2
 for j=1 to 2
 changes[i,j]=|A(i)-A(i+j)|
std=standardDeviation(changes(1,:))
for j=1 to size(changes)
 if(changes(j,1)>=2*std  & changes(j,2) )>=2*std)
                if(changes(j+1,1) & changes(j+2,2)<2*std)
                state change at A(j+2)
END
```

3) Third Algorithm: This algorithm uses the Allan variance in order to find out what will be the length of continuous and equal size intervals that will minimize the standard deviation of the trace. The Allan Variance is a method to analyze a time sequence and eliminate the intrinsic noise in the system as a function of the averaging time. The basic idea is divide a long sequence of into various intervals based on an averaging time. Then the differences of the averages of successive intervals are taken, squared, summed, and divided by a rescaling factor. Our algorithm identify the averaging time that produce the minimum standard deviation and divide the original trace in n/averaging time intervals, where n represents the amount of data points in the trace.

C. Building States Library

After obtaining the state changes per appliances, the averages of those states were used to build a library that correlates a power consumption value with the operating state. The

```
stateChange3(A)
BEGIN
tau= allanVariance(A)
i=1, upperTau=tau;
while upperTau<=size(A)
        averages=[averages;mean(A(i:upperTau))]
        stds=[stds;std(A(i:upperTau))]
        i=i+tau;
        upperTau=i+tau-1
if(i<size(A))
        averages=[averages;mean(A(i:size(A)))]
stds=[stds;std(A(i:size(A))];
    for i=1 to size(averages)-1
        if(|averages(i+1)-averages(i)|>=2*stds(i))
                calculate greater Δ between two points
                state change at that point
END
```

obtained library shall be use to identify which combination of states sum up to a certain aggregate trace power consumption value.

D. Subset-sum Approach

We will use the subset sum approach in order to obtain possible combination of states in the library, that sum up to a certain value in the aggregate power trace. The subset sum problem, is to determine from a set S, if there is a non-empty subset m that its elements sump up to a certain value v. In our perspective, the set S will be the state library, the value v will be the value of the aggregate trace current state, and m is a possible combination of states that sum up to /textitv. The issue is that there can be multiple combinations of states that can sum up to a specific value and we need to develop a filtering mechanism to reduce those options. Our next approach will be to identify the transitions and the probabilities of those transitions to occur.

E. Transition Identification and Probabilistics State Machine

In order to filter the output of the subset sum approach, we will need to identify the transitions of every appliance, calculate the probability of a transition and develop a probabilistic finite state machine for every appliance. The algorithm to filter the possible combinations will need a certain threshold value of probability, in order to keep the combinations greater than that value and dismiss the others. It is also necessary to determine how much history of previous combinations is needed to conserve in order to not lose accuracy in the process of determining the right combination. During this work, we could not reach the point of identifying clear and repetitive transitions, specifically in laptops.

IV. Results

A. Obtained Library

The obtained library has 13 states, being a MacBook Pro laptop the appliance with more states. We can observe the overlapping of power consumption for different appliances and states. This is why it is required to develop another discriminating technique, that will help to differentiate between states. Moreover, there are states of the same appliance that the power levels are just 2 watts in difference, bringing the question of whether is the same state with some source of error, or it is actually that the power was consumed by different internal components of the appliance, producing a different power consumption behavior.

17	MacBook State 1
20	MacBook State 2
24	MacBook State 3
24	Lenovo T61
24	LCD 50% Brightness
32	LCD 100% Brightness
34	MacBook State 4
37	MacBook State 5
40	MacBook State 6
45	MacBook State 3
47	MacBook State 8
52	MacBook State 9
62	MacBook State 10
66	MacBook State 11

B. State Changes Algorithms

The graph representation of the state changes identified by algorithms one, two, and three are shown in Fig. 2 (a),(b), and (c) respectively. The first algorithm was the worst identifying state changes because it was sensitive to peaks because of the limited amount of points used in the calculation. On the other hand, the second algorithm presented better results, due to the increase of information to determine if there was a change (two previous points, and the two subsequent points). However, the best results were obtained using the third algorithm. The sensitivity to noise using the third algorithm is greatly reduce. This is expected because that was the initial purpose of the Allan variance, to remove the intrinsic noise in a system as a function of the averaging time. A disadvantage of the third algorithm is the opposite, when the original trace has a slow variance, like LCD traces, it identified an excess of states changes. This is because the variance of the intervals will be close to zero, and when the algorithm compares the averages changes of consecutive interval, the difference is usually greater than zero. When the variance of the traces are close to zero, it is better to use the second algorithm to obtain better results.

C. Subset-sum Approach

The subset sum approach algorithm was able to identify all the possible combinations that sum up to a specific value of an aggregate trace. However, the set of possible combinations need to be filtered until the real present states are inferred by the algorithm. The next step after obtaining the combination of states subset, is to utilize the probabilistic state machine of each appliance present in the combination.

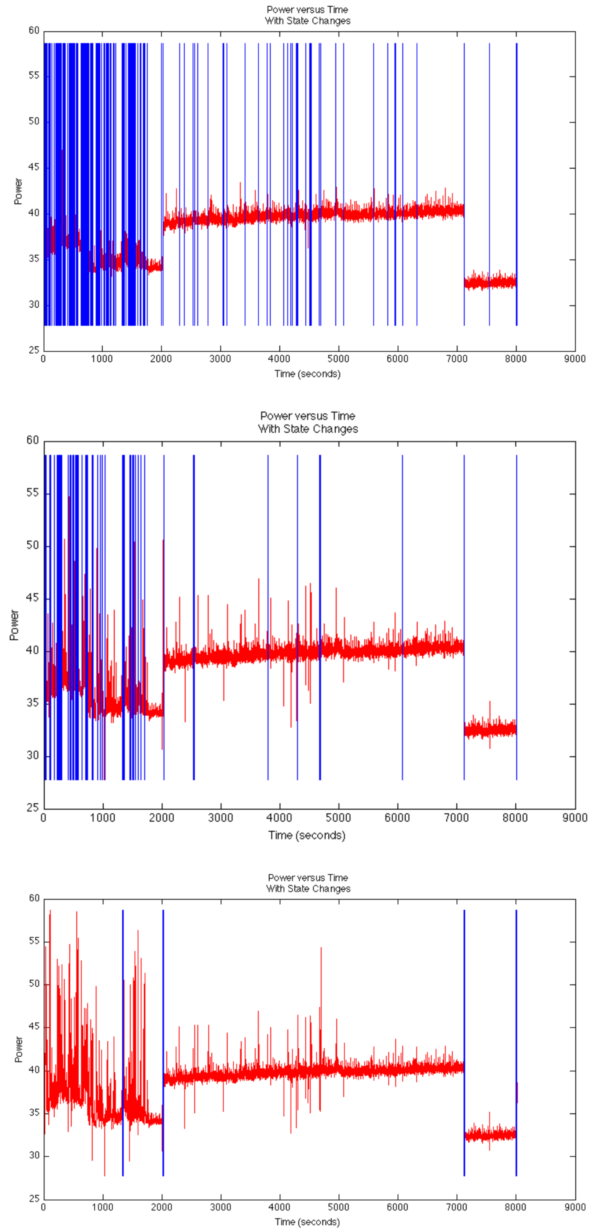

Fig. 4. The graphs show the results of states identification algorithms. State changes are represented by vertical blue lines. (a)First algorithm. (b) Second algorithm. (c)Third Algorithm.

V. Conclusion and Future Work

The usage of strategically located wireless sensor devices for monitoring the energy consumption in buildings, in combination with effective non-intrusive load monitoring approaches will help to obtain more detailed information that will be useful to develop energy conservation policies. During our work, we have work in identifying the operating states of two class of appliances usually present in a building: LCDs and laptops. The process of identifying the operating states of appliances as LCDs, resulted in a simple task due to the low variability that the power trace presents. Besides, that is not the case of laptops. Their power trace ends up being an aggregation of all the components such as CPU, LCD, cooling fan, etc. The process of identify an operating state of a device like a laptop is a non-straightfoward issue. As a future work, another approach could be to calculate the Fast Fourier Transform (FFT) to identify the frequency components during a small period of time of a state transition. The combination of frequency components of an appliance can be used as another discriminating parameter. In addition, the development of the probabilistic state machine of appliances transitions. Finally, it would be of great utility to determine if it is possible to identify transitions and be able to identify states in near-real-time.

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