Poster Abstract: Appliance Classification and Energy Management Using Multi-Modal Sensing

Abstract

In this demonstration, we introduce a low-cost energy management system that tracks appliance energy usage and identifies particular sources of waste that can be optimized. In order to better understand appliance usage patterns, we correlate electrical load information with environmental sensors to identify clusters. These patterns can be used to identify when devices are accidentally left active in unoccupied rooms and provide a means to identify excessive consumption. The correlation is based on learned information over time and hence requires minimal manual labeling. Our system combines measurements from a circuit-panel energy meter with multiple low-cost wireless sensors. We utilize an EMF-based appliance state detector that when combined with circuit-panel and plug-load energy meters allows the system to track the energy consumption of loads at a lower cost and in a less invasive manner than previous metering systems. We deployed our system in a house, collecting data from over 60 sensing points for more than six months. During this period, the system was able to identify wasteful energy usage as high as 17% of the total daily consumption.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; D.2.8 [**Software Engineering**]: Metrics—*complexity measures, performance measures*

General Terms

Building Energy Management, Energy Waste Detection

Keywords

Wireless Sensor Networks, Building Energy Management

1 Introduction

We present a hybrid low-cost monitoring system that combines circuit-panel measurements along with distributed multi-modal sensing across the home. Panel-level measurements are time synchronized with a wireless sensor network to locally infer appliances change states. We utilize a low-cost electromagnetic field (EMF) sensor based on [1], which can monitor appliance usage when placed within close proximity of the device. The EMF event detector locally processes both magnetic and electric field strength data to determine when significant changes have occurred. This data is then relayed back to a custom three-phase meter using a wireless sensor network, where changes in the total power consumption of the house are used to determine the power usage of the appliance that caused it.

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Once appliance usage data has been collected, the next important challenge is to identify energy waste within the home so as to provide users with suggestions for optimization. Examples of energy waste include lights being left on in unoccupied rooms, windows or doors left open allowing hot or cold air to be lost, appliances slowly degrading in performance over time and so-called phantom loads associated with inefficient electronic wakeup circuits. Many of these sources of waste are unique to one particular environment. In response, we present two techniques based on statistical patterns and correlation between sensors as a starting point for a generalized waste detection framework. The first technique correlates electrical load usage with occupancy sensors to establish a relationship that can identify when loads are left running in unoccupied areas of a building. The second technique monitors individual appliances over time in an attempt to recognize anomalous behavior. In both of these cases, the goal is to provide users with meaningful information about where energy is being wasted as opposed to simply displaying energy plots over time.

We deployed our energy management system in a house, collecting data for over 6 months. The configuration consists of a custom three-phase power meter connected to the two phases of the building along with a collection of motion detectors, environmental sensors and EMF detectors. Sensors were placed to provide distinct coverage of each room in the living space. An embedded Linux gateway is connected over Ethernet or wireless to provide Internet access for the system. This same gateway is responsible for receiving the data from different sensors and analyzing it to identify usage patterns and possible waste scenarios, as well as implement NILM algorithms based on [2]. Users were able to label appliances associated with each energy meter and name the various sensors with human-readable descriptions through a web interface.

2 Load Classification

Appliances can be broadly categorized based on how they consume energy in relation to their interaction with users. We decided on these three categories:

- **Background Appliances:** These appliances are either always active, or operate periodically without significant input from the user.
- **Active Appliances:** These appliances are ones that are typically used in the presence of a user.
- **Passive Appliances:** These appliances are typically started by a user, but then continue to execute for a spe-

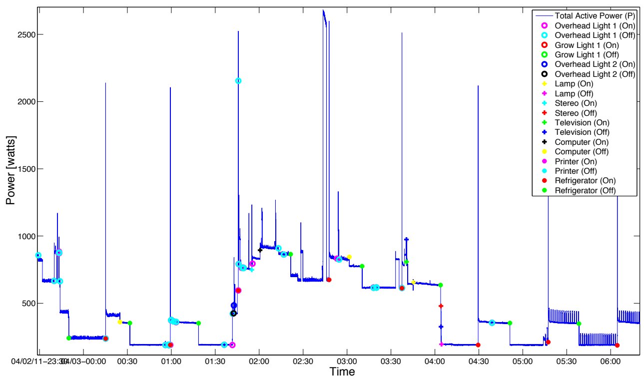

Figure 1. 24 hours of data for an apartment unit, showing events detected and total power consumption.

cific period of time without user intervention.

Based on data from motion sensors in the home, our system is able to classify each load into one of these categories.

3 System Performance

Figure 1 shows the total power consumption for a period of 24 hours, along with the events that were generated from all of the sensor nodes distributed around the dwelling. We see clear correlations between environmental triggers and changes in overall power that can be used to train NILM systems.

3.1 Waste Classification

Using historical data collected by the gateway, each motion detector was correlated with all metered electrical appliances in the home, as described in [3]. If the electrical usage was significantly correlated with a particular motion sensor, it was considered a good indication that the appliance is physically co-located with the device. Devices like overhead lights that are typically used while there is motion in the room tend to be better correlated with the motion sensors in those rooms. Appliances like washers or dryers will have a high correlation during initial activation, but after the user leaves the room they continue to run without motion. The correlation between signals from each motion detector and each electrical appliance automatically finds these associations over time without requiring the user to explicitly linking them. Figure 2 shows the relationship between various sensors in one of our test deployments. The shape of the box corresponds to the sensor type. Each link was selected based on low p-values for testing the hypothesis of no correlation, and hence indicated a strong linkage between the sensors. The length of the link corresponds to the correlation coefficient value where higher correlation are represented with smaller links. We can see that most related devices are clustered reasonably well. Once the mapping between active appliance usage and motion data is established, these data streams are monitored and will log anytime an appliance is being used for more than 15 minutes without any accompanying motion.Table 3.1 shows the average daily energy breakdown and classification of appliances in our test bed. We see that lighting and TV were, on an average day, left unattended for 29.65% and 16.4% of the time, respectively. We computed the total waste detected as compared to the overall power to be as high as 17% on certain days.

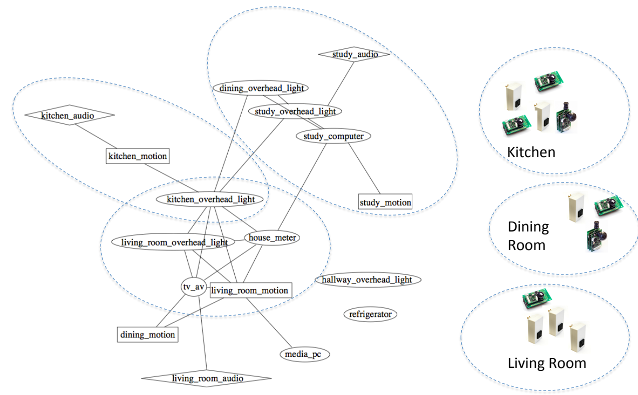

Figure 2. Clustering of sensors where each link represents a significant correlation with shorter links signifying stronger correlations.

Appliance	Daily Energy (WH)	Estimated Waste	Appliance Class
Lights	1076	29.65%	Active
TV	1974	16.4%	Active
Refrigerator	987	N/A	Background
Dish Washer	471	N/A	Passive
Washing Machine	438	N/A	Passive
Clothes Dryer	502	N/A	Passive
Media PC	2015	N/A	Background
Desktop PC	412	24%	Active

Table 1. Detected waste by appliance type.

4 References

[1] Anthony Rowe, Mario Berges, and Raj Rajkumar. Contactless sensing of appliance state transitions through variations in electromagnetic fields. In *Proceedings of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building*, BuildSys '10, pages 19–24, New York, NY, USA, 2010. ACM.

[2] Berges, Mario, Ethan Goldman, Lucio Soibelman, H. Scott Matthews, Kyle Anderson . User-centric non-intrusive electricity load monitoring for residential buildings. *ASCE Journal of Computing in Civil Engineering*, 2011.

[3] Anthony Rowe, Mario E. Berges, Gaurav Bhatia, Ethan Goldman, Raj Rajkumar, James H. Garrett, Jos M. F. Moura, and Lucio Soibelman. Sensor andrew: Large-scale campus-wide sensing and actuation. *IBM Journal of Research and Development*, 55(1.2):6:1 – 6:14, January 2011.