Towards using Low-Cost Opportunistic Energy Sensing for Promoting Energy Conservation

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Abstract. This position paper discusses how to leverage low-cost energy sensing to opportunistically develop activity-based approaches to energy conservation. Based on our extensive experience developing low-cost sensing infrastructures and long-term deployment of ecofeedback systems, we discuss the possibility of unobtrusively inferring domestic activities from the overall aggregated energy consumption of households. We then postulate how the combination of this information with daily household activities could lead to more effective and meaningful ways to re-aggregate residential energy consumption for the purpose of ecofeedback. Here we briefly present a practical approach towards this new research direction that leverages HCI related methods, in particular using the day reconstruction method to provide semi-supervised approaches for automatic detection of household activities.

1 Introduction

Following the vision of the Internet of Things, household devices and appliances such as mobile phones, TVs, refrigerators, and even kettles and toothbrushes are increasingly endowed with more powerful computation, sensing, and communication capabilities. These “smart” devices can provide valuable information about the environment and the activities taking place around them. For instance electricity meters, environmental sensors, surveillance cameras and thermostats can be used to infer on-going households activities (e.g., cooking, cleaning, washing, leisure, etc.) and provide estimates of weekly and even daily occupancy of households.

In this position paper we describe our initial research results looking at how to leverage non-intrusive load monitoring (NILM) technology to opportunistically develop activity-based approaches to energy conservation. Here we combine sensing information from a NILM system, which includes energy consumption, energy events and user interaction events, with family routines obtained through daily reconstruction method. By sensing human activities and learning how these drive the use of energy in households, we aim to facilitate future scenarios that could provide meaningful activity based feedback. We speculate that our approach could provide recommendations and/or automation possibilities, including optimizing micro-generation and off-the-grid household scenarios.

2 Related Work

In many domains (e.g., face recognition) the publicly availability of datasets was fundamental in improving machine learning and data mining techniques. Currently the fields of energy, environment and sustainability research are also seeing the emergence of publicly available datasets. Within these areas the Non-Intrusive Load Monitoring (NILM) community is particularly prominent given the need for extensive use of machine learning and data mining techniques.

Research in this field aims at disaggregating and estimating the consumption of individual appliances by means of applying machine learning techniques to the aggregated consumption signals [1]. NILM public datasets are expected to help researchers create more systematic evaluation processes that can be used across the different existing approaches. Moreover, as current research related to the human side of energy monitoring suggests, householders tend to associate their consumption with everyday activities (e.g. cooking, leisure, cleaning) [2]. We anticipate that future research will attempt to leverage the potential of existing datasets to automatically recognized and extract these activities.

Activity recognition is a long-established field of research. Previous work looked at human trajectories, interactions with objects or social activities [3]. However, with the exception of [4], most approaches neither target energy conservation, nor use the electricity consumption as an input variable for the recognition of human household activities.

3 Combining Consumption and User Activities

Our approach tries to tackle the known limitations of current ecofeedback systems, which focus on increasing efficiency by raising end user awareness of how their actions impact the use of energy. Our previous research showed that energy disaggregation strategies, commonly used in ecofeedback systems, are overwhelming for most users that lose interest and show relapsing behaviors in their energy conservation actions [5]. From the initial challenge of creating effective low-cost disaggregation strategies we faced the new problem of generating meaningful strategies to re-aggregate consumption data that could effectively lead to long-term sustainable energy conservation practices in domestic environments.

3.1 Low-cost Non-intrusive Sensing of Consumption

NILM is considered a low cost alternative to attaching individual sensors on each appliance. Our research group developed a hardware and software platform [6] to enable the quick deployment of long and short-term studies of ecofeedback technology and at the same time serve as a research platform for developing NILM algorithms and techniques, as well as annotated public datasets [7]. The research involved several deployments of different ecofeedback systems, including both qualitative and quantitative evaluation of the user interactions. The overall goal was to raise the understanding and the awareness towards motivating people to consume more sustainably.

Our hardware/software platform evolved according to the requirements of the different deployments. From our initial setup was located in the mains and the ecofeedback was provided on-site (Figure 1 – left), it was later expanded into a full-fledge sensing platform with a dedicated multi-channel DAQ for multiple household studies of the long-term effects of ecofeedback (Figure 1 – right).

Figure 1. Low-cost NILM sensing system: single-house (left), multi-house (right)

3.2 Collecting Activities: Day Reconstruction Method

The Day Reconstruction Method (DRM) [8] is a well known survey method for characterizing daily life experiences. Users are asked to reconstruct their activities and experiences of the previous day without the burden of having to systematically use memory to remember past event, thus reducing the recall bias. The DRM can be thought of as a two step process: (i) users are asked to keep a diary of the previous day where they will list activities as being a sequence of episodes; (ii) every episode listed in the diary is then described by answering a series of questions about the situation and the feelings that they have experienced.

3.3 Research Questions

By combining low-costs NILM sensing with DRM we can focus on household activities to gain a better understanding of how and when energy is consumed and (micro) generated in a domestic environment. In this context the following research question emerges:

RQ1. Can we unobtrusively infer domestic activities from the overall aggregated energy consumption of the household?

Previous research in activity recognition typically uses data from a variety of sensors (e.g., presence, sound, cameras, etc.), which involves a dedicated infrastructure that in turn requires additional costs, energy consumption, management and maintenance. We instead intend to use an opportunistic approach based on our NILM infrastructure, weather and other environmental sensors and device-level consumption data and additional sensors for ground truth and calibration. We anticipate that in the future this data could be accessible by smart appliances. Therefore an additional research question emerges:

RQ2. Are domestic activities a more effective and meaningful way to re-aggregate residential energy consumption for the purpose of ecofeedback?

Regardless of the known shortcomings of ecofeedback systems [5], research demonstrated several important findings in terms of guidelines for information presentation. For instance it is known that traditional kWh representation (or even CO2) is not an adequate form of feedback in particular when presented in large aggregated monthly data. Conversely displaying appliance level consumption information is overwhelming and ineffective, as users tend to lose interest in detailed information relapsing to previous behaviors. With this research question we aim at investigating if re-aggregating consumption by domestic activity is more meaningful and effective as a basis for ecofeedback strategies and also for generating recommendation for energy conservation.

4 Exploratory Research

In order to test the feasibility of our approach we used our own NILM Dataset combined with data collected using the DRM in one of the actual deployments from our research.

4.1 SustData Dataset

The SustData dataset (freely available at http://aveiro.m-iti.org/data/sustdata) contains over 50 million individual records of electric energy related data, spanning a total of 1144 distinct days since July 2010 coming out of four distinct deployments of our sensing infrastructure. Currently the dataset contains over 11 million individual power events across all the four deployments. As stated in [7] a quick inspection of the results immediately reveals the high values for the daily standard deviation, which is a clear indicator of the large difference in the number of power events across the different houses, for instance, in the second deployment four houses have over 1000 daily power events on average, while seven houses have less than 300 power events per day. More detailed analysis (see Figure 2) provides a clear mapping between energy consumption and power events throughout different periods of the day and the week. We conducted additional analysis correlating family size and other independent variables leading to some interesting patterns among different families and households. For instance as reported in [5] there is a correlation between consumption, power events and the presence of children in the household, but not, for instance, between households with three or four people.

Day Name \ Hour	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Monday	3	3	2	3	2	2	3	10	3	3	2	2	1	2	2	2	3	2	3	3	4	2	2	3
Tuesday	3	2	3	2	2	3	2	3	3	3	2	3	1	2	3	3	3	3	2	19	7	2	4	2
Wednesday	2	3	3	1	2	2	2	2	10	5	2	3	79	88	3	5	3	2	3	5	3	3	3	3
Thursday	2	2	2	2	2	3	3	82	113	2	2	3	3	6	4	2	3	2	4	28	5	47	50	4
Friday	3	1	2	3	3	2	2	3	3	2	2	3	75	89	3	3	2	2	2	12	69	63	54	3
Saturday	2	2	2	2	2	1	2	2	2	3	97	243	64	6	3	6	11	1	2	3	2	3	12	15
Sunday	3	3	2	2	1	3	3	1	2	3	3	3	2	7	10	3	2	2	4	1	2	4	5	2
Week	2	2	2	2	2	2	2	15	20	3	16	39	34	30	4	3	3	2	3	12	15	19	19	4

Figure 2. Average Consumption (color coded) and Power Events (nr.) for one Household (# 22) per Day of the Week and Hour of the Day

4.2 Family Activities

Datasets like SustData are becoming more popular and present an opportunity to explore opportunistic sensing of human activities. However collecting ground truth for human activities, in particular for long periods is difficult. Either the resident needs to keep record of all the activities, which is not convenient, or additional sensors are needed (for instance cameras or plug-level sensors) to label each activity, which is costly and not practical.

Role in family: daughter **Age:** 11 **Activity:** watch TV **Category:** entertainment **Start:** 12:30 **End:** 13:00 **Devices:** TV **Location:** living room **Mother Location:** outside of the house **Father Location:** kitchen **Other kid location:** bedroom	**Role in family:** mother **Age:** 33 **Activity:** clean kitchen **Category:** cleaning **Start:** 21:20 **End:** 21:35 **Devices:** lights kitchen, lights living room, TV **Location:** living room **Father Location:** living room **Kid location:** living room

Figure 3. Examples of Activities

The study reported in [9] consisted of two parts: a) a 1-day diary of all members of the family followed by b) interviews the day after. Using the Day Reconstruction Method (DRM) [6], we asked all family members to list, in a chronological order, the activities they performed while being within the house during the reported day. For each activity they provided a brief name and start and end time. Following the complete reconstruction of all daily activities, participants were asked to provide more detailed information for each activity (see Figure 3). This information was: a) electrical devices that were directly or indirectly used in the activity, b) all family members' locations (kitchen, living room, bedroom, outside house, other part of house).

A total of 12 families participated in this study and reported on a total of 15 different activities that used 28 different appliances. These activities were later grouped into seven categories as shown in table 1, highlighting some interesting patterns in the family activities. For example, it becomes evident that some activities are much more common than others (watch TV was mentioned 22 times whereas working out and cleaning air were only mentioned once each). Likewise, it is also possible to see that some activity categories are much more prominent than others, particularly the entertainment and having a meal categories that together account for roughly 60% of the mentioned activities and use about 57% of the listed appliances.

Category	Activity (occurrences)	Appliances
Cleaning	Wash dishes (3) Dehumidify air (1)	Dishwasher; Dehumidifier
Entertainment	Play (8) Watch TV (22)	Unknown game console; Wii game console; PlayStation game console; Television; Personal Computer
Exercise	Workout (1)	Treadmill; Television
Laundry	Wash Clothes (2) Iron Clothes (3)	Washing Machine; Iron
Meal	Breakfast (13) Lunch (3) Dinner (12)	Microwave; Coffee grinder; Coffee machine; Kettle; Stove; Oven; Bottle heater; Fridge; Television; Personal computer; Toaster; Smoke extractor
Personal Care	Shower (4) Dry Hair (10)	Water heater; Smoke extractor; Fan
Work	Study (2) Work (13)	Personal computer; Laptop; Television

Table 1. Activities grouped by category

On average each house reported 12 activities (SD = 3,46), yet some houses were more active than others (e.g., house #22 reported 17 activities during the day, four houses reported nine activities, whereas on the lower end, house #2 reported only four activities). A more detailed analysis (see Figure 4) provides a clear mapping between energy (consumption and power events), user activities and appliances for two of the families that took part in the diary study. This analysis revealed some interesting usage patterns for some appliances, namely the TV that appears associated with several different activities (watch TV, play, leisure, lunch and dinner).

Likewise, this kind of analysis also suggests that families may not report all their daily activities. This is particularly evident in the house on the left side of Figure 4, which at 23:00 shows 40 power events that are not reflected in the reported activities (such a high number of power events would normally be associate with a cycling appliance like a clothes washer, which could indicate activities in the laundry category).

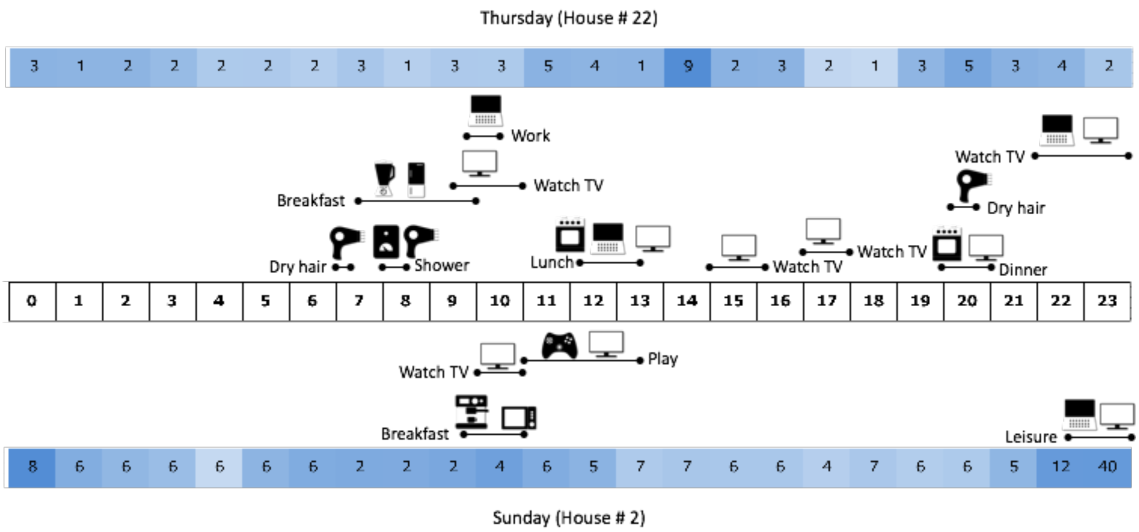

Figure 4: Consumption (color coded), Power Events (nr.), Activities and Appliances for two sample days of the week from two households in SustData

5 Discussion and Conclusion

The main output of this research will be an activity-based sensing approach to energy conservation in domestic environments. By combining NILM with activity based sensing we want to develop approaches to energy conservation that move beyond traditional ecofeedback systems and anticipate distributed micro-generation scenarios leading to important changes in energy sustainability and ultimately the utility business. To this end we anticipate to provide a combination of i) actionable recommendations for energy conservation including those that take advantage of the availability of renewable sources, and ii) suggesting novel approaches for in-house automation that could leverage smart appliances and grid supply / demand balance. Our approach uses domestic activities and production/consumption parity to overcomes the known limitations of traditional ecofeedback systems.

In order to achieve these goals we aim at conduct a test-bed of 100 households to collect aggregated consumption data through our NILM framework, extended with micro-generation data, weather and other environmental parameters and finally appliance level ground truth data to generate semi-automatic labels. This data will come from diverse socio-economical backgrounds and will enhance our existing SustData public dataset [7] to provide the research community with a powerful tool to conduct additional research in the field of energy conservation. The final objective is to contribute to enhance the state of the art in ecofeedback technologies from opportunistic activity based sensing of domestic human activities related to energy.

6 References

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