Understanding domestic appliance use through their linkages to common activities

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Abstract

Activities are a descriptive term for the common ways households spend their time. Examples include Daily routines such as cooking, doing laundry, and Computing. Smart energy meter data can be used to generate time profiles of activities that are meaningful to households' own lived experience. Activities are therefore a lens through which energy feedback to households can be made salient and understandable. This paper demonstrates how hourly time profiles of household activities can be inferred from smart energy meter data, supplemented by appliance monitors and environmental sensors. In-depth interviews and home surveys are used to identify appliances and devices used for a range of activities. These relationships between technologies and activities are captured in an 'activity ontology' that can be applied to smart meter data to make inferences on hourly time profiles of up to nine everyday activities. Results are presented from six homes participating in a UK trial of smart home technologies. The duration of activities and when they are carried out is examined within households. The time profile of domestic activities has routine characteristics but these tend to vary widely between households with different socio-demographic characteristics. Analysing the energy consumption associated with different activities leads to a useful means of providing activity-itemised energy feedback, and also reveals certain households to be high energy-using across a range of activities.

1 Introduction

Using remote monitoring to identify when, for how long, and how often different activities take place in the home as part of everyday life is of increasing interest, now smart meters, sensors and monitors are becoming more widely available. These activity recognition efforts have mainly been focused on healthcare applications, including assisted living and tele-rehabilitation. Designing and deploying sensing technology to reliably identify key activities associated with health monitoring usually involves multiple sensors ranging from switch/pressure sensors to occupancy sensors, sensors for measuring walking patterns, physiological condition, different wearable sensors, and environmental sensors.

With the emergence of smart homes and home energy management systems (HEMS), autonomous activity recognition is recognised as an important enabler of home automation more generally. In this paper, we propose an approach for domestic activity identification based on smart energy meter data only. With large-scale roll-outs of smart meters that have already occurred or are about to occur in many countries worldwide, domestic activity identification based on smart meter data becomes very attractive as it does not require any additional sensors and relies on using already available data collected for energy monitoring and billing purposes. As well as enabling advanced HEMS, activity recognition using smart meter can also be used to provide meaningful and timely energy feedback, since it yields insight into households' activities and their consequences for energy consumption.

This paper develops an activity-centric approach to understanding energy use in terms of the time profiles of activities, both routine and non-routine, that constitute the majority of life at home. This approach can be applied to provide novel and effective forms of energy feedback. The overall aim is to improve the value of HEMS by disaggregating the total energy consumption measured by the smart meter and linking these disaggregated data to domestic activities. This builds on previous work in which we propose an algorithm for domestic activity identification using smart meter data and demonstrate its potential using one test house [1]. In [2], we extend this approach by integrating qualitative data from household interviews and physical home surveys into the activity recognition process, and illustrate this multi-step methodology on two case study homes. In this paper, we focus on scaling up the activity recognition methodology and providing a detailed analysis of empirical findings with respect to temporal variation of activities and their energy usage patterns. We use data from six households with different socio-demographics, and analyse the temporal consistency or variability of activities within a household, as well as the extent of activity time synchronisation across households.

The paper is organized as follows: Section 2 provides a background to activity recognition using smart energy meter data. Section 3 describes the methodology developed in [1, 2]. Section 4 describes the results using data from six homes participating in a field trial of smart home technologies in Loughborough, UK. Results are presented in terms of activity time-use profiles both within household and between households. Section 5 discusses the key findings and concludes the paper.

2 Background

Domestic activities are what people do at home. Common activities or 'doings' include washing, cooking, laundry, cleaning, watching TV, playing computer games, resting, and so on. Activities may be routine or irregular, may vary or stay consistent between week and weekend, and may involve one or all household members [3].

Activities are meaningful, since households think about their own daily lives at home in terms of activities; they are salient or easy-to-recall; they are appropriate in providing a comprehensive account of life at home; and they are useful as they are associated with decisions and actions that can be influenced by interventions or policy measures.

As people readily understand their domestic life in terms of activities, analysing and interpreting energy usage data is an effective means of providing energy feedback to households [2]. Energy consumption can be broken down and linked to domestic activities to enable activity-itemised energy feedback. This is a more meaningful and informative approach to feedback than conventional energy or cost-based methods.

A key technological challenge to successful activity-itemised energy feedback is reliably identifying a wide range of activities from metering data. While identification of domestic activities using remote sensing has been an active research area for some time, activity identification based on smart meter data has emerged only recently.

Related research has quantified energy services consumed in homes [4,5] or the energy consumption of specific appliances and devices [6]. Such approaches often supplement aggregated smart meter data with plug monitors for specific appliances and environmental and motion sensors to detect occupancy or specific activities such as cooking, washing, or heating [7]. Data gathering can be both sensor-intensive and intrusive, as in cooker-mounted webcams [7].

Our approach uses smart meters that measure the aggregate load and plug monitors that measure individual appliance loads. This is supplemented by non-intrusive appliance load monitoring (NALM) [8, 9, 10, 11], which disaggregates the aggregate load down to specific appliances, using purely data analytical software-based methods. While most NALM approaches rely on high-sampling rate smart meter data, our NALM approach [12] uses low-sampling rate active power data only, sampled at no more than 6sec intervals, akin to smart meter deployments across the UK and Europe.

This is in line with assisted living applications using NALM and smart energy meter data to support patients with Alzheimer's disease living in smart homes [10]. This application uses high sampling rates (~60Hz) and active and reactive power to identify usage of particular appliances, but appliance usage is not related to specific activities. Also in the assisted living domain, [13] propose an approach for detecting activities using NALM, smart energy meter data, and individual plug monitors, identifying activities such as shopping, media, food preparation, telephoning, and hygiene.

In contrast with these assisted living applications, our approach relies on very low sampling rates, mimicking smart meters that will be or have already been deployed at national scales. Our approach also focuses on identifying activities linked to energy consumption as a basis for effective energy feedback.

3 Methodology

We develop an activity recognition algorithm by identifying appliance usage events via NALM [12] and by defining activity ontologies using qualitative data from interviews and physical home surveys. In this section, we briefly describe the resulting multi-step methodology, and discuss the challenges associated with activity recognition from readily available data, and how our methodology addresses these challenges. An extended explanation of the methodology is presented in the previous work [2] and is summarised here:

1. Define a set of energy-oriented activities to characterise everyday life at home.
2. Collect real-time energy and environmental data using energy monitors and environmental sensors. Collect data on home and household characteristics including appliance ownership and use patterns.
3. Disaggregate energy data (NALM) [12].
4. Map relationships between activities and technologies to build an 'activities ontology'.
5. Make activity inferences from disaggregated real-time data using activities ontology [1].
6. Validate inferences using time diaries and household visits.

3.1 Activity selection

The set of activities that is usually studied in energy-related research is narrowly focused on high consuming activities such as cooking or lighting [4]. In line with the UK's Office of National Statistics (ONS) time-use study [14], and discussed in [2], we identify 16 activities that are comprehensive, parsimonious, and energy oriented and group them into 4 categories: Daily Routines, Interacting, Computing and Leisure, and Other Activities. Daily Routines category comprises 6 activities: cooking, eating, washing, laundering, cleaning and sleeping. Interacting consists of communicating (with people outside the home) and socialising (with people at home). Computer and Leisure consists of 4 activities: watching TV, listening to radio or music, playing computer games, and all other computing. Other Activities consists of the 4 remaining activities including hobbies, working and caring.

3.2 Data collection

In each monitored house, a mix of quantitative and qualitative data is collected. Quantitative data comprises aggregate active power in Watts (W) sampled every 6-8 seconds, and (optionally) environmental data such as temperature, humidity and occupancy to detect activities that do not primarily use electricity, such as washing using gas-based water heating, or cooking on a gas hob. In addition to aggregate power, we also measure up to nine appliances using plug monitors.

Collected qualitative data comprise: (1) physical home surveys; (2) semi-structured household interviews on activities and video ethnography on technology ownership and usage. The interview and video data are coded (analysed and interpreted) in terms of domestic routines and are used primarily for mapping relationships between activities and technologies into an 'activities ontology' for each household. Home surveys provide the spatial layout of rooms and devices, and help towards building the ontology. The appliance time diaries and electricity data are used for the disaggregation and activity inference algorithms, described further below. Details of our data collection platform can be found in [15].

3.3 Energy disaggregation

The task of Non-intrusive Appliance Load Monitoring (NALM) is to disaggregate a household's total energy readings down to specific appliances used. NALM effectively creates virtual power sensors at each appliance using purely software tools. Many NALM methods have been proposed in the literature, that mainly consist of edge detection and feature extraction, followed by classification. NALM research, especially on active power loads at low sampling rates (lower frequency than 1Hz), is still challenging with 70% or less accuracy in real household environments with many appliances. A review of approaches is given in [9]. In this paper, we use the approach proposed in [12] based on decision tree (DT), which has the advantages of minimal training and high performance at low sampling rates of active power data only. The Decision Tree (DT)-based method of [12] consists of training and testing phases. During training, for each known appliance maximum upraising and decreasing edge is recorded and used to design a decision tree. Labelling of signatures detected by the NALM algorithm is dependent on data from individual plugs or/and self-completed appliance time diaries. The output of testing is a list of appliances used together with the start and end time of their operation. Output is validated in a subsample of homes against self-completed time diaries by householders recording the frequency and duration of appliance usage (appliance time diaries).

3.4 Activities ontology

The output of NALM, i.e., the list of specific appliances used with their timestamps, together with data from individual appliance monitors (IAMs) can be mapped to particular activities through the use of ‘activity ontologies’. An activity ontology maps out all known relationships between activities and the energy-using technologies (devices, appliances) used in those activities. The ontology also captures relationships between activities or technologies and other environmental information such as occupancy of particular rooms, temperature/humidity change, etc. The purpose of the ontology is to link measurable real-time information to the set of activities characterising everyday life at home.

A particular energy-using technology can *definitely, possibly,* or *indirectly* indicate that an activity is occurring. These are distinguished in the ontology through codes for *marker technology, auxiliary technology,* and *associated activity,* respectively. Whereas marker and auxiliary technologies allow activity inferences with different degrees of certainty, the ‘associated activity’ relationships allow inferences about activities that are otherwise not indicated by technology use. An associated activity refers to the use of technology that is a marker for another activity, which is concurrent or linked with a second activity (e.g., switching off bed lamp at night might indicate going to sleep, hence it is an associated technology for the 'sleeping' activity).

An example of part of an ontology is shown in Figure 1 in matrix form (ontologies can also be represented diagrammatically). The rows in the ontology refer to technologies and the columns to activities. Activities are grouped into the four categories of Daily Routines, Interacting, Computing and Leisure, and Other Activities. Activities are traffic-light colour coded such that green indicates an activity can definitely be inferred, red indicates that an activity is not inferable from the current data, and amber refers to an activity that can possibly be inferred if readings are available from IAMs since the technology cannot be reliably inferred by the NALM algorithm.

The mapping of relationships between technologies and activities (each cell of the matrix in Figure 1) show marker technology as an ‘x’, auxiliary technology as a ‘~’ and associated activity as a ‘o’. Each technology contains a descriptor of its location and a small narrative regarding when and how often the technology is used based on the qualitative data. Narrative data shown in green font is from the video ethnography; narrative data shown in red font is from the validation visit (see Step 6 on pp.3).

	ACTIVITIES																TECHNOLOGY-ACTIVITY RELATIONSHSIPS - additional info			
	Daily Routines						interacting		Computing and Leisure				Other Activities							
TECHNOLOGIES	cooking	eating	washing	laundering	cleaning	sleeping	communicating	socialising	tv	radio	games	computing	hobbies	caring	working	other	Location / Room	Fixed / Mobile	When Used	Frequence of Use
breadmaker	x																kitchen	(fixed)	after dinner	3 times / week
toaster	x	o															kitchen	(fixed)	breakfast	
omelette maker	x																kitchen	(fixed)		
fridge	x																kitchen	fixed		
crockpot	x																kitchen	(fixed)		
microwave	x	o															kitchen	fixed	breakfast - porridge (the only thing microwave is use	
kettle	x	o						o									kitchen	(fixed)		
food mixer	x																kitchen	(fixed)		
electric oven & hob with extractor fa	x																kitchen	fixed		
dishwasher	x																kitchen	fixed	2-3am	Every night from 2am-ish
washing machine				x													kitchen	fixed	Overnight	Several times a week
tumble dryer				x													kitchen	fixed		
DAB radio	~	~		~ [ ]						x							kitchen	(fixed)		on in background all day (t=
gas fire																	lounge	fixed		
stereo, speakers										x							lounge	(fixed)	every day (t=4.00)	during cup of tea in afterno
VHS VCR								~	x								lounge	(fixed)		
PVR (= hard drive?)								~	x								lounge	(fixed)		
TV								~	x				o	NA [~]			lounge	(fixed)		
record player								~		x							lounge	(fixed)	once a week (t=4.00)	
TV								~	x								dining room	(fixed)		if there's a clash of schedul
DVD player								~	x								dining room	(fixed)		
catch-up TV								~	x								dining room	(fixed)	not used very much (t=1.50)	

Figure 1: Example of part of an activity ontology.

3.5 Activity inferences

The NALM algorithm introduces some uncertainty, due to possible mis-classification if a power signature of one appliance is classified as another due to similarity of active power signatures. Another source of uncertainty comes from the stochastic nature of human behaviour, which is common to other domestic activity recognition studies. These uncertainties are called disaggregation uncertainty and context uncertainty, respectively [1].

To make reliable inferences given these uncertainties, we use Dempster-Shafer (DS) Theory of evidence (see [1]). DS is a proven to be effective in case of high uncertainty and multiple sources of information; it can make the distinction between uncertain and unknown information and combine evidence from different sources to reach a consensus with some degree of belief.

Disaggregation uncertainty, estimated during NALM training, and context uncertainty, obtained heuristically using the activity sample data, are integrated into the model as in [1]. Further details on the activity inference algorithms are provided in [1].

3.6 Inference validation

The final step of the methodology validates inferred activity data in semi-structured interviews with households in which inferences are compared against self-completed time diaries for the same period [2]. Discrepancies are identified and attributed, most commonly to missing time diary entries or to inference inaccuracies linked to mis-specifications in the activity ontologies. These are then corrected as shown by the red cell entries in Figure 1. In some cases, the final validation step identifies activities that do not occur in a particular household. These can then be removed from the ontology (see light red columns in Figure 1).

3.7 Practical challenges and solutions

Not all domestic activities are inferable using the proposed methodology with available energy data. Activities cannot be detected if they are not tied to an energy-consuming technology, if they do not have a marker technology, or if they are only associated with technologies that cannot be reliably detected due to, for example, low power operation. The set of activities that cannot be detected reliably varies from household to household, but generally always includes sleeping, eating, socialising and caring.

Our approach faces a number of challenges similar to those in the existing body of research on energy disaggregation and appliance usage. Table 1 lists how we address each of these challenges.

Table 1: Challenges in activity recognition and our approach.

Challenges	**Our approach**
<u>Knowability:</u> Activities cannot be inferred if they lack any direct or indirect association with energy-using devices or with specific and measurable environmental conditions (e.g., motion in particular rooms).	*Time diaries cover full set of activities (but only for specific days). Ontology distinguishes associated technologies which mark an activity taking place at the same time as another activity.*
<u>Reliability</u>: Disaggregation routines cannot consistently capture the use of devices that are highly mobile or that operate on battery power (either permanently or while not plugged in). Conventional distinctions between audio, visual, communication, and computing devices are rapidly collapsing. This increases the difficulty of making inferences about specific types of ICT-related activities.	*Mobile or battery-powered devices are not used as marker technologies in ontology. ICT-based activities can be collapsed into a higher order 'all ICT-related' activity to reduce risk of missing inferences.*
<u>Ambiguity</u>: Devices used for several different activities cannot be used unambiguously in making activity inferences.	*Ontology distinguishes marker from auxiliary technologies. Marker technologies identify when an activity is definitely going on. Auxiliary technologies identify when an activity may be going on.*
<u>Validity</u>: Inferences made about energy services or appliance use from disaggregation routines	*Self-completion time diaries and structured time-diary based interviews are used to validate activity*

have unknown reliability (accuracy) or validity in terms of households' lived experience (appropriateness).	*inferences.*
Coverage: Heating and lighting are both energy-intensive services but not activities *per se*. Heating and lighting-related energy use could be apportioned to activities taking place in specific rooms for time periods during which those rooms are lit or heated, or could be accounted for separately.	*Heating- and lighting-related energy is included in separate energy service categories when inferences are expressed in energy terms (rather than as time-use profiles).*
Accuracy: Extracting individual appliance usage from data with Smart Metering Equipment Technical Specification (SMETS) specifications [14], i.e., active aggregate power only at very low sampling rate of the order of 10 seconds is tricky because some appliance signatures are the same, or some signatures are too low-power and 'hidden' by other appliances concurrently operating.	*Data checking & cleaning, building library of known appliance signatures, using appliance survey, developing new non-intrusive appliance load monitoring algorithms that can detect with accuracy >80% individual appliance loads from one-dimensional and low resolution data, and appliances overlapping in time use.*
Accountability: The accuracy of the disaggregated energy use as virtual sensors must be used as evidence towards making a decision towards inferring an activity.	*Using a probabilistic approach towards combining evidence from multiple heterogeneous sensors to infer activities, incorporate and discount uncertainty from incorrectly identified appliance events, reliable ontology.*

4 Results

In this section, we apply our approach to make inferences about activities taking place in six households over a period of one month (October 2014). We have chosen this month since it is not typically associated with holidays, periods or absence from homes, or other obvious disruptions to routine domestic life. Our main aim is to demonstrate the potential of our approach by examining the time profiles of household activities in terms of their timing, duration, and consistency day to day and week to week within a given household, as well as between different households. These time-use profiles are a necessary step to understanding and representing energy use in ways that are meaningful to households as a basis for feedback.

The monitored houses are of different occupancy and age groups (e.g., retirees, working couples, families with children). These households were chosen with a mix of technical and non-technical backgrounds, and were fitted with energy monitoring equipment (total gas, total electricity, and electricity for up to 9 individual appliances (IAMs) via submetering), environmental sensors and smart home kit to automate/pre-schedule appliance and heating use.

Table 2 provides a brief description of the six households, and the activities we could infer using the active power data (aggregate and appliance-specific) and home surveys. No time diaries of appliance use were available for all households, which had implications on disaggregation certainty, since we could not verify some appliance signatures.

The sixth column of Table 2 shows the percentage of electrical appliances out of the total number (shown in the third column) of known measurable electrical appliances in each home that could be detected reliably via our NALM algorithm (column 5) or directly metered from a plug monitor (column 4). We can detect at least 48% of appliances in most houses, but as the range of appliances increases, we are limited by our signature database, which contains all signatures we have been able to label via submetered devices, or time diaries from previous validation work. (Time diaries of appliance use were not available for the homes in Table 2.) In all cases, NALM significantly supplemented IAM to detect almost 50% of commonly used appliances in the households, as well as identifying auxiliary technologies (inc. minimum demand or base load) to identify activities such as eating and sleeping.

Table 2: Household characteristics, appliance detection, and activities that can be inferred with different levels of uncertainty.

Household ID	**Household Size & Composition**	**Total number of known measurable electrical appliances**	**Total number of appliances detected by IAM**	**Total number of appliances detected by NALM**	**Appliance Detection (% of known appliances in home)**	**Inferable Activities** **(n = total number of inferable activities for each household)**
2	Family of four with two young children	17	9	5	82	Cooking, eating, washing, laundering, sleeping, socialising, watching TV, listening to radio (n=8)
4	Couple of pensioners	55	14	18	58	Cooking, eating, laundering, watching TV, sleeping, hobbies, computing (n=7)
5	Family of four with two children in early teens	44	14	7	48	Cooking, eating, laundering, sleeping, watching TV, cleaning, computing, hobbies (n=8)
8	Couple of pensioners	43	11	12	53	Cooking, eating, washing, laundering, cleaning, sleeping, watching TV, computing (n=8)
10	Family of four with two young children	34	9	8	50	Cooking, eating, washing, laundering, sleeping, watching TV, computing (n=7)
19	Family of four with two children in early teens	32	10	10	63	Cooking, eating, laundering, sleeping, socialising, watching TV, listening to radio, ICT-related games (n=8)

While we can detect most high load appliances, those low power appliances (<20W) such as electric toothbrush, printer, router, DAB radio get 'lost' in the aggregate data and account for the percentage of appliances that cannot be detected. Another set of appliances that we cannot detect, and are not included in the above total, are gas-based, battery-based and mobile appliances such as smart phones, tablets, radios and digital cameras.

We build activity ontologies for each of the six households using data from the home survey, household interviews and video ethnography. Table 2 shows all activities that can be identified based on the detected appliances mapped to these activities in the ontology. We can detect in most cases all six activities of daily routines, all activities of ICT-related leisure, and in some cases socialising, hobbies and games. Socialising is partly inferred from the quantitative data gathered from Listening to radio, but could be inferred with higher certainty if we had more qualitative data describing patterns of socialising and/or appliances associated with socialising for the household. We can only detect low load appliances, such as the CD player, associated with the Listening to radio activity in House 2, because it is submetered.

In the following sections, we summarise our main results in response to three questions:

1) *When and for how long do activities occur each day?* We use stacked time duration plots to show average activity time profiles (including durations) during a day over the week and weekend, for each household.

2) *How consistent are the occurrences and durations of activities over time?* We use rose charts to show averaged monthly time durations of activities across hourly time slots.

3) *Can activity time profiles provide meaningful feedback on energy use?* We use data tables to show the total energy consumption per month per activity for all the households.

The first two sets of results show the time profile of activities and their consistency both within and between households. This is important for analysing the potential flexibility to shift or sequence certain activities in order to manage energy demand. The third set of results identifies the main "activity consumers" of energy, and so the potential for providing tailored activity-itemised energy feedback.

4.1 Activity time profiles per household for typical days

Using Houses 4 and 5 as examples, Figures 2 and 3 show the time use over the activities detected for the two households, as a percentage of the total known time use, for an average weekday and an average weekend day during October 2014.

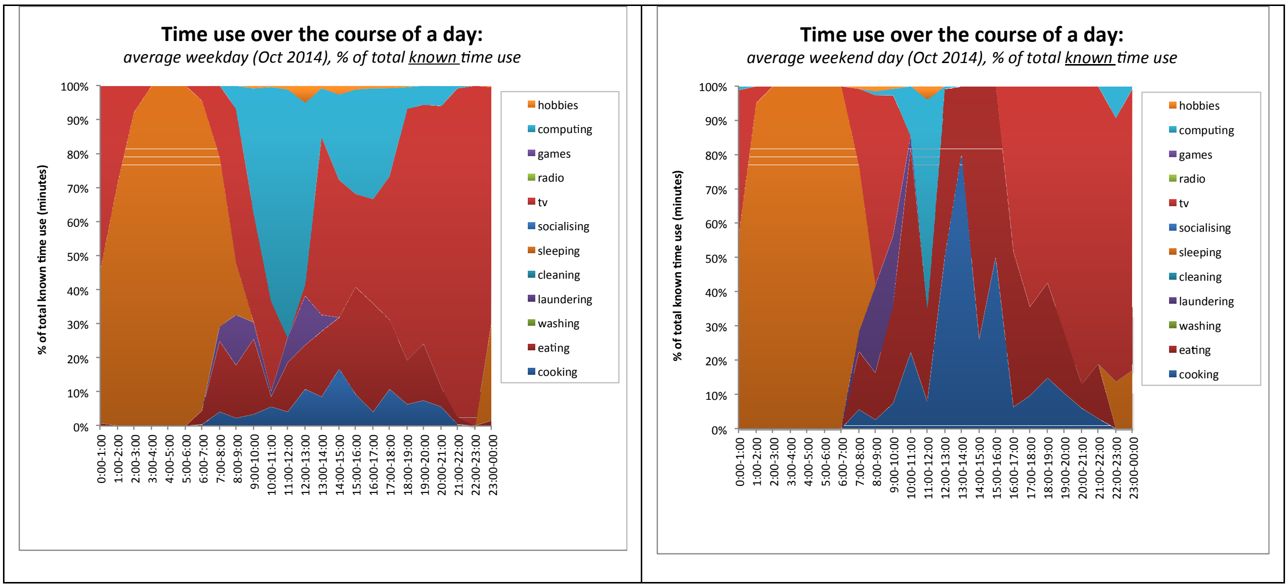


Figure 2: House 4 average weekday and weekend activity time profiles.

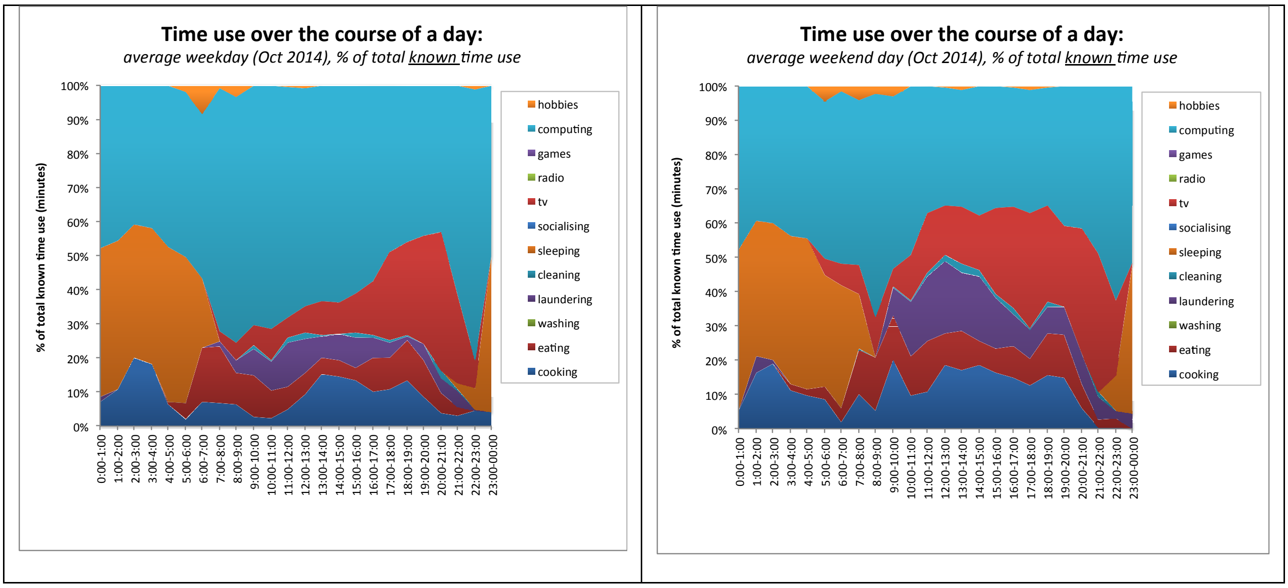


Figure 3: House 5 average weekday and weekend activity time profiles.

House 4 is occupied by a couple of pensioners. The household wakes up every day between 6-7am, and the TV is being left on throughout the day until the late night during weekdays. During weekends, on the other hand, there is markedly less TV watching, less computing, whereas time is allocated more to cooking and eating.

House 5 is a family with two teenage children. Cooking shows marked variation from weekday to weekend, reflecting the changing domestic routines of a household with school age children and working adults not at home during weekdays. Cooking activities at the weekend are more frequent and of longer duration spread throughout the day (Figure 3). We also see that House 5 runs its dishwasher overnight, hence we observe a large time duration of the 'cooking' activity between midnight and 6am. Cooking includes preparing food and drink but also cleaning and washing up afterwards.

A similar variation is seen in the watching TV activity between weekday and weekend, again reflecting a household with children and so a distinctive temporal pattern of meal times, TV watching, and bed time routines which differ markedly on school nights compared to weekends (Figure 3).

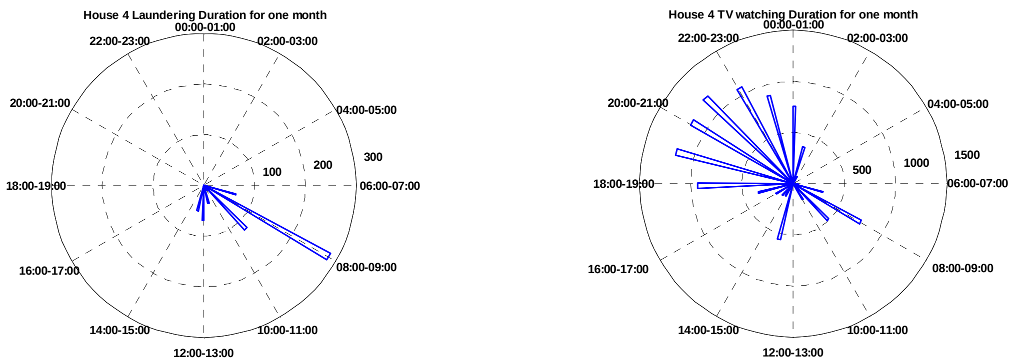
4.2 Typical durations of daily activities, averaged over a month

Figures 4-6 show the distribution of particular activities over a 24 hour daily cycle divided into labelled hourly time slots, beginning at 00:00 and moving clockwise through the morning, afternoon, evening, and night time periods, for Houses 4 and 8, respectively. The radii of the bins in these ‘rose diagrams’ are sized differently according to the activity. All bins show duration in minutes over a month (October 2014).

Both Houses 4 and 8 have the same household composition: two pensioners. The results show key activities which have different roles in households' routines: laundering, computing, TV watching, washing. While washing and laundering are activities in the 'Daily Routine' category of everyday necessities at home, TV watching is a leisure activity, and computing as an activity can be variably linked to work, study, gaming, information search, shopping, communication and so on**.**

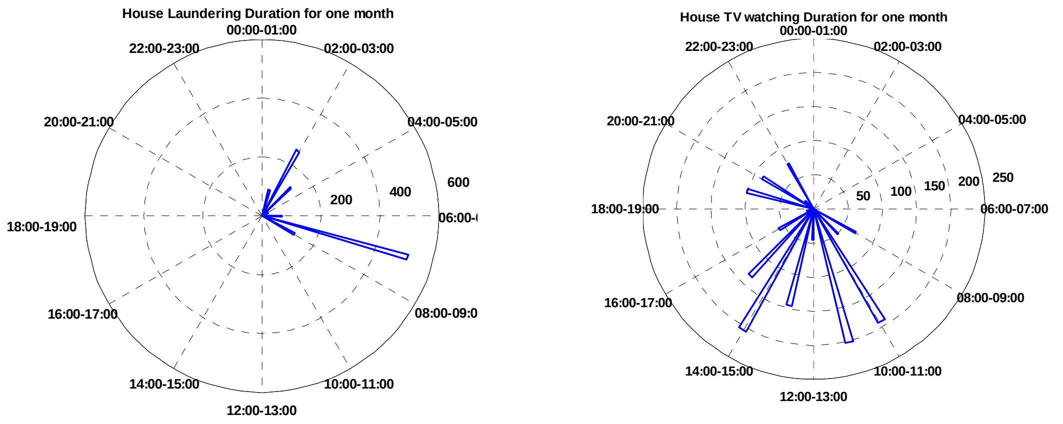
House 4 is occupied by two retired adults who are mostly at home during the day, with the TV on throughout the day intermittently. Laundering occurs mostly in the morning as shown in Figure 4. Computing occurs regularly throughout the day, but predominantly in the morning, compared to House 8, also occupied by a couple of retirees, as shown in Figure 6.

In House 8 there is no laundering activity in the afternoons and evenings (see Figure 5). Instead laundering takes place overnight and in the early hours of the morning as the household is on an Economy 7 tariff and benefits from cheaper overnight tariffs by shifting loads to off-peak hours. House 8 has the same composition as House 4 (two pensioners) and is similarly occupied during the day with the TV on throughout the day intermittently.



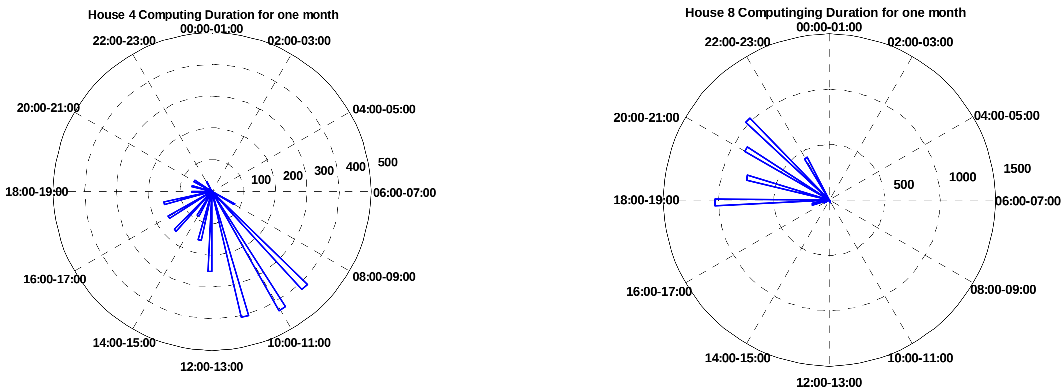
(a) Laundering (b) TV watching

Figure 4: Total time duration of activities (minutes) in House 4 over a period of one month per hourly time slot: (a) laundering, (b) TV watching.



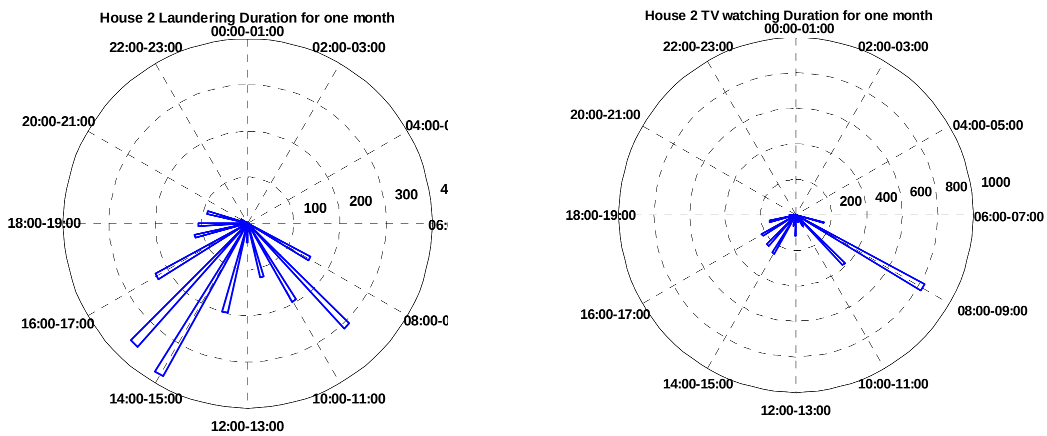
(a) Laundering (b) TV watching

Figure 5: Total time duration of activities (minutes) in House 8 over a period of one month per hourly time slot: (a) laundering, (b) TV watching.



(a) Computing in House 4 (b) Computing in House 8

Figure 6: Total time duration of Computing (minutes) in Houses 4 and 8 over a period of one month per hourly time slot.

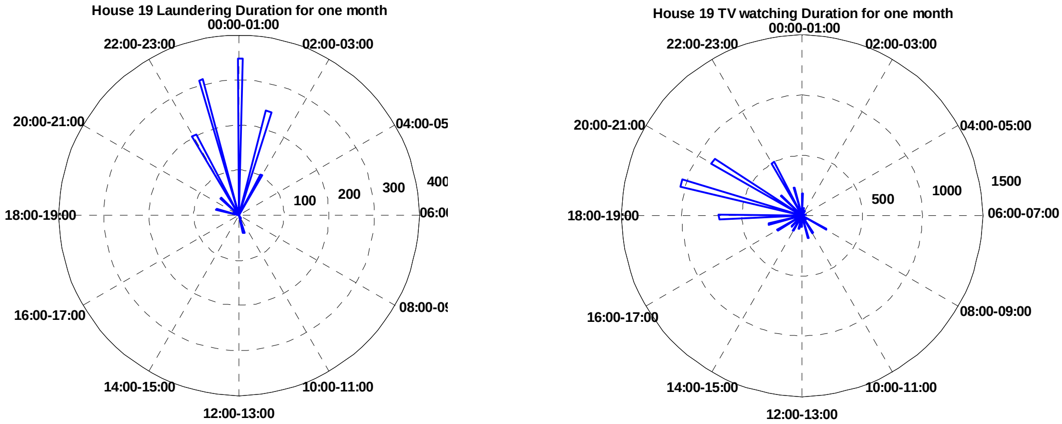


(a) Laundering (b) TV watching

Figure 7: Total time duration of activities (minutes) in House 2 over a period of one month per hourly time slot: (a) laundering, (b) TV watching.

House 2 has a different composition: two adults and two pre-school children. In House 2, the need for laundering created by young children becomes very clear (see Figure 7). Laundering activities are distributed throughout the day for relatively shorter durations than House 4, with the bulk of laundering taking place in the afternoon. The rose diagram also makes clear the importance of the TV watching morning routine in the 8-9am time slot.

House 19, a family with teenage children, like House 2 also does more laundering than Houses 4 and 8 with only retired adults, but the laundering activity takes place late at night (see Figure 8). TV watching is limited to evenings, after a day at school, work and various after-school activities.



(a) laundering (b) TV watching

Figure 8: Total time duration of activities (minutes) in House 19 over a period of one month per hourly time slot: (a) laundering, (b) TV watching.

Table 3 compares the cooking activity pattern across all 6 houses. Houses 4 and 8 cook a bit less than other houses which matches the households' composition. All houses spend more time on cooking on an average weekend day compared to an average weekday. Both Houses 2 and 10, with young children, spend a higher portion of their time on cooking with respect to other inferred activities compared to Houses 4 and 8, occupied by a couple of retirees.

Table 3: Cooking activity duration in all 6 houses over a month

House	House 2	House 4	House 5	House 8	House10	House 19
cumulative time use (in mins)	286	73	639	162	369	182
% of time spent on cooking over all inferred activities for this household	12.45%	4.25%	10.56%	9.58%	19.76%	8.18%

4.3 Energy consumption per activity

The above results showing time durations of specific activities over typical days or over whole months do not show associated energy consumption. Yet as noted, energy consumption linked to daily activities is an effective basis for providing meaningful energy feedback to households. This may be particularly important for activities over which households have some flexibility as to timings (e.g., shifting loads to off-peak hours) or to durations (reducing loads). The activity inference methodology described above can be used to link part of the electricity consumption of a household to certain activities. This is shown in Table 3 for the six households on which the methodology was tested, where the total energy consumption in kWh over the whole month is disaggregated to the level of activities. Shaded cells represent activities for which we do not have sufficient data to make an inference, e.g., Houses 4, 5, and 19 do not have an electric shower and use hot water from a gas boiler for washing, so the washing activity is not inferable from the available electricity data. Similarly, radio and ICT-related gaming appliances, which have a very low load, can only be obtained via an IAM, present only in Houses 2 and 19.

Table 3: Total electricity consumption per activity (in kWh) for a month.

House / Activity	House 2	House 4	House 5	House 8	House10	House 19
Cooking	75.4 *	33.1	98.3	65.6	67.6 *	37.3 *
Washing	47.7			24.4	1.2	
Laundering	12.9	10.7	79.3	20.3	24.4	4.0
Cleaning			3.8	3.6		
Watching TV	2.8	11.5	17.7	9.7	39.8	19.2
Listening to radio	6.5					0.8
Computing		15.6	68.2	15.6		
ICT-related games						3.4
Hobbies		1.5	11.1			
Total electricity use per house (independent of activity inferences)	337.7	282.3	636.3	422.4	417.0	248.0
% of total electricity use explained by activity inferences (inc. lighting)	44%	26%	44%	33%	32%	26%
Total residual (kWh) per house unexplained by activity inferences	192.4	209.9	357.9	283.2	284.0	183.3
% of residual due to base load	32%	27%	42%	22%	29%	56%
% of residual due to cold appliances	16%	53%	14%	9%	27%	22%

% of total electricity use that cannot be explained by all above (inc. lighting)	30%	15%	25%	46%	30%	16%

* Gas also used for cooking (on a hob).

Of all the activities which are generally inferable from available electricity data, cooking is the main energy-consuming activity. House 5 consumes the most electricity overall, with higher than average demand for computing and laundering. Houses 2, 4 and 19 cook on a gas hob which reduces their electricity consumption for cooking activity.

By relating these values to the time duration of activities, it is possible to benchmark the energy efficiency of appliances in different households. As an example, according to Table 3, House 19 consumes almost 5 times less electricity for laundering than House 8. The activity duration rose plots show that both houses spend about the same amount of time on laundering (see Figures 8 and 5) so it may be that House 19 has a more efficient washing machine than House 8.

Activity recognition cannot account for all the energy use in the home, with a maximum of 44% across the six homes analysed. Homes with electric cookers and showers will have a higher % of total electricity consumption resulting from inferable activities. Electricity that cannot be accounted for using the activity inferences relates to base loads, lighting, cold appliances such as refrigerator, boiler and other battery-operated or low-load appliances that cannot be disaggregated due to the limitations of NALM algorithms operating on very low sampling rate data. Table 3 shows that, after accounting for cold appliances and base load, the unaccounted % of electrical energy consumption drops to less than 46%. House 2, specifically, includes in its 30% unexplained energy consumption, charging of an electric car but we cannot fully disaggregate the entire charging period. Note that these unaccounted numbers include lighting, which in the UK contributes around 16% towards the total consumption [16].

5 Conclusions and Future Work

In this paper, we presented an activity-centric approach to understanding time use and energy use in homes. We tested this approach on six households and provided illustrative results. This approach moves away from a traditional energy-centric approach linked to aggregated energy and cost-related feedback. Activity-centric approaches help users and scientists understand activities in the home in terms of time profiles which are meaningful to households' lived experience.

Our results show that between 4-9 domestic activities can be reliably inferred using electricity data and activity ontologies. These include cooking, laundering, and watching TV. For the six houses on which the method was demonstrated in this paper, 7-8 activities per household could be inferred. Most of the inferable activities have regular weekday time profiles, but weekend activities are less regular. For activities with regular time profiles throughout the week, timings and frequencies tends to change between weekday and weekend. Differences are particularly marked in households with children with associated scheduling of school runs, meal times, TV watching periods, bed times and so on. The timing and duration of activities also varies widely across households.

These results are work ongoing and we plan to do more extensive analysis, both within household and between household, to determine the reliability and implications of our activity-centric approach, and to test its effectiveness as a basis of providing activity-itemised energy feedback to households. We will also develop simplified methodologies for evaluating the quality and accuracy of the activity-inferences.

We plan to develop a self-completion instrument that is less resource intensive and intrusive than the householder interviews which we use to develop the activity ontologies. This will enable our method to be scaled-up alongside a nationwide smart meter roll-out. Specifically: (i) initial household interviews and video ethnography could be substituted by activity-based questionnaires that can be administered by remote or as part of a smart meter installation; (ii) home surveys which could be self-completed by households or carried out by smart meter installers with the households' consent.

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