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Identifying the time profile of everyday activities in the home using smart meter data

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Abstract

Activities are a descriptive term for the common ways households spend their time. Examples include cooking, doing laundry, or socialising. Smart 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 a multi-step methodology for inferring hourly time profiles of ten household activities using smart meter data, supplemented by individual appliance plug monitors and environmental sensors.

First, household interviews, video ethnography, and technology surveys are used to identify appliances and devices in the home, and their roles in specific activities. Second, 'ontologies' are developed to map out the relationships between activities and technologies in the home. One or more technologies may indicate the occurrence of certain activities. Third, data from smart meters, plug monitors and sensor data are collected. Smart meter data measuring aggregate electricity use are disaggregated and processed together with the plug monitor and sensor data to identify when and for how long different activities are occurring. Sensor data are particularly useful for activities that are not always associated with an energy-using device. Fourth, the ontologies are applied to the disaggregated data to make inferences on hourly time profiles of ten everyday activities. These include washing, doing laundry, watching TV (reliably inferred), and cleaning, socialising, working (inferred with uncertainties). Fifth, activity time diaries and structured interviews are used to validate both the ontologies and the inferred activity time profiles.

Two case study homes are used to illustrate the methodology using data collected as part of a UK trial of smart home technologies. The methodology is demonstrated to produce reliable time profiles of a range of domestic activities that are meaningful to households. The methodology also emphasises the value of integrating coded interview and video ethnography data into both the development of the activity inference process.

Introduction

Smart meters & real-time energy feedback

A national smart meter rollout programme is underway in the UK (Jennings 2013). The European Electricity Directive requires EU member states to deploy smart meters to 80% of end-users by 2020. Smart meters are an integral element of the regulatory and governance response to energy system challenges:

A shift to smarter grids, with smart meters and smarter market design, is seen as key to accommodating innovation in environmental technologies and energy services, managing costs through increased consumer participation and ensuring an increased demand side contribution, while at the same time widening consumer choice and improving consumer understanding and management of their consumption. (Connor et al. 2014)

Design specifications for smart meters in the UK require a minimum of half-hourly readings for electricity and gas to be collected by energy supply companies via wide area networks, and half-hourly gas and 10 second electricity readings to be accessible by end-users via home area networks. The close-to-real time electricity readings and the half-hourly gas readings can be visualised using energy monitors or displays.

Feedback is important "*in making energy more visible and more amenable to understanding and control*" (Darby 2006). The effect of feeding back real-time information on energy consumption to households has been extensively studied. A systematic review of field experiments to test behaviour change interventions in homes found that the majority used information to provide feedback (RAND Europe 2012). Darby (2006) found studies providing direct feedback using displays achieved energy savings of 5-15%. A recent meta-analysis found an average of 11% savings from intervention studies using real-time feedback (Delmas et al. 2013).

Large-scale market trials in the UK between 2007 and 2010 involved over 60,000 households of which 18,000 had smart meters. The combination of smart meters and in-home displays consistently resulted in energy savings of around 3% (AECOM 2011). Analogous trials in North America found similar levels of savings (Darby 2010).

Displays are particularly useful for showing the energy consequences of routine, daily behaviours (e.g., cooking, laundering) and non-heating end-uses. The effect of one-off behaviours (e.g., installing insulation) is more meaningfully shown on periodic bills (Darby 2010). Real-time displays can also provide historic comparisons using data from analogous past time periods (AECOM 2011). There are different interpretations of how and why feedback works. Darby (2010) summarises these as:

- <u>sociological</u>: feedback makes energy more visible and brings it within the perceived control of end-users
- <u>economic</u>: feedback enables end-users to make informed, goal-oriented (e.g., cost-minimising) decisions
- <u>psychological</u>: feedback provides a salient stimulus to which end-users pay attention and respond
- <u>educational</u>: feedback supports energy-savings as a skill learned through experience

The economic and psychological perspective characterises most feedback studies. Both rely on an energy-focused or 'resource-centric' approach in which information fed back directly concerns energy consumption (Bates et al. 2012). The sociological perspective shifts the emphasis from energy use to households' lived experience. The role of feedback is in making salient energy use in terms of the routines, habits and activities that constitute the majority of life at home. Fischer (2008) finds that the more clearly end-users can interpret their energy use in terms of specific activities, the more clearly they can relate their energy bills to their daily behaviour.

Activities as a lens for providing energy feedback

This paper takes an activity-centric approach to analysing and interpreting information on energy use in homes. This approach can be applied to smart meter-enabled real-time feedback.

In simple terms, activities are what people do at home. Examples include cooking, laundering, socialising, entertaining. Activities provide a valuable lens through which to interpret and provide feedback on household energy use because activities are:

- <u>meaningful</u>: households think about their own daily lives at home in terms of activities
- <u>salient</u>: activities are noticeable, easy-to-recall features of domestic life
- <u>appropriate</u>: activities provide a comprehensive account of life at home matched closely to households' lived experiences
- <u>useful</u>: activities are, by definition, actionable through decisions and behaviour that can potentially be altered

Activity-centric research has only recently been linked to energy-related research. A major challenge is how to interpret real-time energy data in terms of activities as a potential first step towards providing activity-related energy feedback to households with smart meters.

Objective and overview of paper

The objective of this paper is to demonstrate the value of an activity-centric perspective on domestic energy use. This objective is premised on activities being a meaningful, salient, appropriate, and useful way of feeding back information to households on their daily lives. To achieve this objective, we develop, test, and validate a multi-step methodology for making robust inferences about the daily time profiles of activities in households with smart meters.

Literature Review

Activities, practices and energy services

Domestic life is inherently energetic (Lutzenhiser 2002). But from a sociological perspective, individuals do not consume energy. Rather, energy provides useful services that enable normal and socially acceptable activities to be carried out as part of everyday life at home. It is the 'doings' of everyday life that have consequences for energy and material consumption (Røpke 2009). Most energy-intensive activities in homes are quite mundane: watching TV to relax or entertain; running appliances to freeze food or dry clothes; heating water for washing. Comfort, convenience, and cleanliness have become normalised expectations embedded in such activities, with significant consequences for energy use (Shove 2003). Røpke (2009) observes that if asked about their everyday life, people will usually describe what activities or 'doings' they are engaged in. Cooking, washing, caring (for children or elderly household members), and resting are all examples of activities (see Figure 1). Activities are linked to time use as we discuss further below. Activities unfold over time with distinctive patterns, frequencies and durations. Many activities also involve energy-using technologies or "*material artefacts*". But the use of devices, appliances or technologies as part of an activity does not necessarily make explicit its energy or resource consumption. In-home displays providing real-time feedback can make electricity use explicit but only in an aggregated form that is neither salient nor linked to the activities that are meaningful to households.

It is important to emphasise the differences between this activity-centric perspective and sociological research on practices. Characterising domestic life in terms of activities is primarily descriptive. Practice-based analysis is concerned with explaining why, when and how life at home is organised (e.g., Strengers et al. 2014). Social practices are bundles of 'sayings and doings' that are enacted or performed and so reproduced through time and space, as well as socially (Gram-Hanssen 2011). Shove and Pantzar (2005) proposed practices as being constituted by three elements and their inter-relationships. These three elements are competences, meanings, and products (or technologies). Gram-Hanssen (2011) included institutionalised knowledge and explicit rules as a fourth element of practice. This decomposition of practices into constitutive elements is a common way of analysing the unfolding of domestic life. Practices explain the patterns of change, rhythm, and synchronicity which "*pervade everyday life, providing temporal structures that organise and order repetitions within the complex, ongoing flow of the social world"* (Walker 2014).

Practices not people are the focus; people are 'recruited' by such practices as part of their performance and so reproduction. In turn, these practices explain energy use: "*the use of energy is an 'ingredient' of the doing or performing of social practices*" (Walker et al. 2014). Energy services play a mediating role: "*the demand for energy is … a secondary outcome of demands for energy services, which are in turn a consequence of how everyday practices are constituted and performed*" (Walker 2014).

'Energy services' are thus a third lens through which to examine energy use in homes. Energy services are useful functions provided by the end-use conversion of final energy into useful energy (Grubler et al. 2012). Unlike activities and practices, energy services are directly concerned with energy conversion; but like activities and practices, energy services emphasise the useful role of energy as part of domestic life.

In this paper, we develop an activity-centric perspective on domestic life as it provides a lens through which to provide meaningful feedback to households on energy use. The purpose of this short literature review is to situate this activity-centric perspective in relation to practice-based and energy service-based analysis. Figure 1 summarises the key features of these three approaches. As the examples in Figure 1 show, the terms cooking and washing fit the definitions of all three terms, although with different emphases and meaning. Cooking as an activity describes how a household uses its time. Cooking as a practice can be analysed in terms of its constituent elements. Cooking as an energy service describes the conversion of gas or electricity into heat to provide sustenance. Heating and lighting are also clearly energy services. But neither are activities *per se*. As a simple heuristic, activities are responses to the enquiry: 'tell me about your day at home'. It is unlikely that a response would be: 'I spent the day heating and lighting my home'. Yet a warm and lit home clearly enables many other activities. From an activity-centric perspective, heating and lighting are enabling energy services.

activities	practices	energy services
things people do, ways people describe their day or how they spend their time	*socially-shared bundles of doings and sayings constituted by technologies, skills, meanings and rules*	*useful functions provided by energy end-use technologies*
e.g. cooking, washing, resting, caring	e.g. cooking, washing, socialising	e.g. cooking, washing, heating, lighting
descriptive characterisation of everyday life in a way that is meaningful to households	theory-based analysis of constitutive elements of everyday life	ultimate purposes for which energy is consumed as part of everyday life

Figure 1. Illustration of Key Terms: Activities, Practices, Energy Services

Activities and time-use studies

An activity-centric perspective on energy consumed as part of everyday life relates strongly to time-use studies. In households' lived experiences, activities (as well as affective states) are closely linked with time:

"Time is experienced and recalled as durations, or elapsed time, spent in various activities and with various sorts of feelings … Since all human states and activities occupy time, an appropriately designed time-use survey instrument can provide a comprehensive account of rhythm and balance among all the conditions and circumstance of daily life." (Gershuny 2011)

Time spent on activities can be measured in four ways: conventional questionnaires, opportunity sampling (e.g., beeper studies), direct observation, and time diaries (Gershuny 2011; Durand-Daubin 2013). Time diaries are the most common instrument, recording information on activities and their sequencing (who does what, when?) as well as the duration of activities or their time budgets (how much of each activity?) (Gershuny 2011).

Time-use statistics are collected nationally. Most EU member states are involved in the Harmonised European Time-Use Study (HETUS) using standardized time-use survey instruments (Eurostat 1999). The UK's Office of National Statistics (ONS) carried out its major time-use study as part of this project in 2000/1 (ONS 2000a). More recently, the ONS has administered simpler, reduced-form time-use studies on smaller samples.

The UK's time-use surveys use an 'activities' terminology. Self-completion instructions in the surveys are worded as follows:

What were you doing? *Please record your main activity for each 10-minute period.*
[All activities that people might do are important. However uninteresting or routine you feel that something is please write it in.]

Analysis of national time-use statistics, collected in time diaries, shows aggregate patterns of activities over daily, weekly, monthly and seasonal rhythms. In the UK, for example, national time-diary data from 2005 shows eating, personal care, housework, and free time (particularly watching TV or listening to music) to be the main types of within-home activity on weekdays, apart from sleeping and resting. An average of 70% of time was spent at home (Lader et al. 2006).

Daily time-use profiles similarly provide a useful means of capturing and visualising patterns of domestic activity. This is the approach taken in this paper as part of an activity-centric perspective on everyday life and its energy-using consequences.

Inferring activities from smart meter data

Smart meters are making available real-time data on energy consumption in homes. These data can be analysed to better understand domestic activities and their energy-using consequences. Data analysis techniques seek to identify and characterise human behaviour using disaggregation algorithms (Zoha et al. 2012) and probability-based inference algorithms (Clement et al. 2014). Electricity disaggregation via non-intrusive appliance load monitoring (NALM) is a technique for breaking down a home's total or aggregated electricity consumption to the level of individual appliances using only software-based tools, hence 'non-intrusive'. Zoha et al. (2012) provides a recent review of NALM tools. These usually apply probabilistic techniques to autonomously learn appliance signatures (the distinctive features of each appliance's electricity use) and make inferences about appliance usage patterns. For example, Clement et al. (2014) propose an approach for detecting 'activities of daily living' using non-intrusive appliance load monitoring (NALM), smart energy meter data, and individual plugs, but in the context of assistive living. A similar approach is developed by Cho et al. (2010).

Related human-computer interaction (HCI) research has quantified energy services consumed in homes (Bates et al. 2012) or the energy consumption of specific appliances and devices (Froehlich et al. 2011). 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 (Clear et al. 2013b). Data gathering can be both sensor-intensive and intrusive, as in cooker-mounted webcams (Clear et al. 2013a). Regardless of the meter, monitor and sensors used for data gathering, resulting inferences about disaggregated energy services or appliance usage are commonly interpreted using qualitative interview or video data on household routines and behaviours, or on exceptional events identified in the energy data (Bates et al. 2012; Clear et al. 2013b).

Research Approach & Methodology for Inferring Activities

Research approach

The literature reviewed emphasises the potential value to households of interpreting domestic energy use through the lens of activities. The objective of this paper is to demonstrate how this activity-centric approach can be implemented, what data are required, and what its key implications are. Specifically, we develop a multi-step methodology for making robust inferences about the hourly time profiles of activities in households with smart meters. We then test and validate the methodology on two case study households, using both quantitative and qualitative data.

Our research builds on energy disaggregation analysis, as well as work by Liao et al. (2014b) to link disaggregation with inferences about energy activities in a domestic context. We follow the basic approach of using disaggregated smart meter data in combination with plug monitor data to make inferences about household activities, interpreted using qualitative household ethnography. However, we extend this approach in three main ways. First, we make inferences about a comprehensive set of domestic activities rather than a limited set of energy-intensive services. Second, we use qualitative data from household ethnography ex ante, prior to making activity inferences, in order to map relationships between technologies and activities. This integrates qualitative data into a mixed methods approach, rather than using qualitative data only ex post as an interpretive lens through to which explore or explain the results of the inferences. Third, we use non-intrusive appliance load monitoring (NALM) to disaggregate energy consumption from a single smart meter reading with minimal alterations to other infrastructure (Liao et al. 2014a).

Overview of methodology

The multi-step methodology for making activity inferences using smart home data is summarised schematically in Figure 2. The six steps for each household analysed are:

1. Define set of activities to characterise everyday life at home.
2. Map relationships between activities and technologies to build an 'activities ontology'.
3. Collect real-time energy and environmental data using meters, monitors, and sensors.
4. Disaggregate real-time energy data using known appliance signals.
5. Make activity inferences from disaggregated real-time data using activities ontology.
6. Validate inferences using time diaries and household visits.

The six steps involve different sources and types of data, both quantitative and qualitative (see left side of Figure 2). Quantitative data include real-time data from electricity smart meters and appliance plug monitors. Additional data are from environmental sensors (motion, humidity). Qualitative data include semi-structured interview transcripts and video ethnographies of households' use of technology. These qualitative data are coded (analysed and interpreted) in terms of activities and technologies. Additional mixed data are from activity and appliance time diaries self-completed by households. House surveys provide the spatial layout of rooms and devices. The next sections explain each step of the methodology in detail.

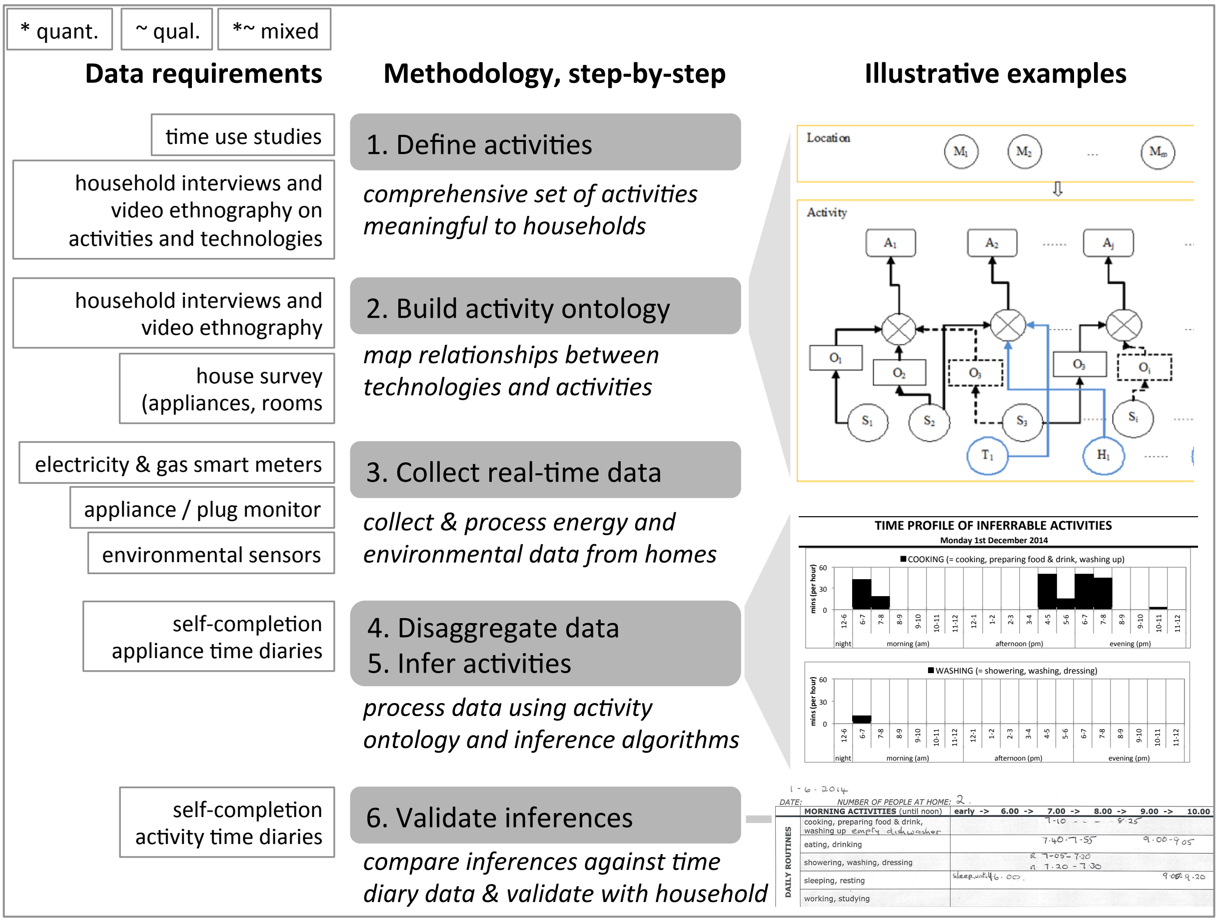

Figure 2. Methodology for making activity inferences using smart home data.

Step 1. Define activities.

The set of activities analysed in energy research tend to be narrow, focusing on activities linked to energy-intensive services) such as cooking, IT-related entertainment, or lighting (Bates et al. 2012). We develop a set of activities for characterising everyday life at home that is:

- comprehensive - so the set of activities corresponded to households' lived experience
- parsimonious - so the set of activities was manageable for the qualitative and quantitative data collection
- energy-oriented - so the set of activities distinguished all energy-using activities in the home (noting the above discussion about heating and lighting not being activities *per se* but rather energy services)

Our set of 16 activities is grouped into 4 categories: Daily Routines, Interacting, Computing & Leisure, and Other Activities (see Table 1). The start point for this set was the long, detailed list of activities coded for in the UK's national time-use studies (ONS 2000b). These were reduced by excluding activities not taking place in the home (e.g., travel, visiting museums), and grouping into 'Other Activities' those taking place within the home only under specific circumstances (e.g., employment, study, volunteering, sport) (Lader et al. 2006).

Activities grouped within the three main categories of 'Daily Routines', 'Interacting', and 'Computing and Leisure', were all identified as important in time-use studies, in our interviews with households on their domestic activities, and in energy-related research.

Activities in the 'Daily Routines' category mapped directly onto ONS activity codes.

The 'Computing and Leisure' category distinguishes four ICT-related activities which are expanding rapidly in terms of associated devices, impact on electricity consumption, and time use (Lader et al. 2006). Other non-ICT leisure activities are captured under 'hobbies' in the 'Other Activities' category.

The 'Interacting' category distinguishes two types of interpersonal communication, either physically within home, or remotely using ICTs. Interpersonal communication is associated with the spread and adoption of technologies (Rogers 2003) and is inherent to activities which share common patterns across households (e.g., meal times).

Table 1. Set of activities characterising everyday life at home. Notes: ONS codes show corresponding activities in UK national time-use study (ONS 2000b). Energy end-use shows main technologies associated with an activity.

Category	Label	Description	ONS codes	Energy end-use
Daily Routines	cooking	cooking, preparing food & drink, washing up	31	cooker, white goods
	eating	eating, drinking	02	-
	washing	showering, washing, dressing	03	[hot water]
	laundering	doing laundry	33	white goods
	cleaning	cleaning, housework *other than laundry or washing up*	31	white goods
	sleeping	sleeping, resting	01,53	-
Interacting	communicating	communicating, interacting with people outside the home	514,724	ICTs
	socialising	entertaining, socialising, being with people at home	510,511,512,513	-
Computing & Leisure	watching tv	watching tv or other audiovisual devices	82	ICTs
	listening to radio	listening to radio, music or other audio devices	83	ICTs
	playing games	playing games on console, computer, tablet, smartphone	733	ICTs
	computing	using computer, tablet, smartphone *other than for games or work*	372,722,723,725	ICTs
	doing hobbies	doing hobbies, sports, games	721,726, 731,732, 734,81	-
Other Activities	caring	looking after children, caring for household members	38,39	-
	working	working, studying (including use of computer)	1,2,4	(ICTs)
	other	other activities	34,35,371,6	(ICTs)
N.B. heating and lighting are additional energy services but are not included as activities *per se*				

Step 2. Build activities ontology.

An activities ontology maps out all known relationships between activities and the energy-using technologies (devices, appliances) used in the activities. The ontology also captures relationships between activities or technologies and other environmental information such as occupancy of particular rooms. The purpose of the ontology is to link measurable real-time information to the set of activities characterising everyday life at home identified in step 1. Figure 3 shows an example of part of an ontology for one household in our sample. This is shown in matrix form. Ontologies can also be represented schematically, as illustrated in Figure 2 (top right).

	ACTIVITIES																	
	daily routines						interacting		computing & leisure				other					
TECHNOLOGIES	cooking	eating	washing	laundering	cleaning	sleeping	communicating	socialising	tv	radio	games	computing	hobbies	caring	working	other	Location / Room	Fixed / Mobile
breadmaker	x																kitchen	(fixed)
microwave	x	o															kitchen	fixed
kettle	x	o						o									kitchen	(fixed)
food mixer	x																kitchen	(fixed)
electric oven & hob	x																kitchen	fixed
dishwasher	x																kitchen	fixed
washing machine				x													kitchen	fixed
tumble dryer				x													kitchen	fixed
VHS VCR								~	x								lounge	(fixed)
TV								~	x				o				lounge	(fixed)
record player								~		x							lounge	(fixed)
TV								~	x								dining room	(fixed)
DVD player								~	x								dining room	(fixed)
catch-up TV								~	x								dining room	(fixed)

Figure 3. Example of part of an activities ontology.

The ontology is constructed using three data sources. First, household interviews and video ethnography are coded in terms of activities and the technologies used in association with those activities. Coded data are then mapped into the columns in the ontology; coded data on technologies are mapped onto the rows (see Figure 3).

Second, house surveys detailing the room configurations and distribution of devices are used to add rows (technologies) to the ontology, add data on the location of technologies, and cross-check against coded interview data. Third, reasonable assumptions are used to populate specific activity-technology relationships if these are self-evident, e.g., a toaster being used for 'cooking'. A particular energy-using technology can definitely, possibly, or indirectly indicate that an activity is occurring. These three different relationships are distinguished in the ontology as follows:

x = marker technology -> use of technology is definite indicator of an activity (e.g. use of oven indicates 'cooking' in Figure 3)

~ = auxiliary technology -> use of technology is possible indicator of an activity (e.g., use of kettle may indicate 'socialising' in Figure 3)

o = associated activity -> use of technology is a marker for another activity which is linked in time with an activity (e.g., use of TV may indicate 'socialising' in Figure 3 as this occurs concurrently with 'watching TV').

Marker technologies allow activity inferences with a high degree of certainty. Auxiliary technologies allow activity inferences but with uncertainty. An auxiliary technology may indicate an activity, but not necessarily. Auxiliary technologies are not integral to an activity. They may be used in some circumstances and not in others (e.g., a kettle may be used as part of 'socialising' but may be used not as part of 'socialising'). Including kettle as an auxiliary technology for 'socialising' in the ontology does not imply one is more likely than the other. The 'associated activity' relationships allow inferences about activities that are otherwise not indicated by technology usage. An example from Figure 3 is 'socialising' with people inside the home which does not inherently require a technology, but may involve one. As an example, members of a household may collectively watch television as part of 'socialising'. So the television is a marker technology for 'watching TV', but also provides an 'associated activity' relationship to 'socialising'. The ontology also includes available information on the location of activities or technologies, on whether the technologies are fixed or mobile, and on the frequency and duration of activities in general terms (not shown in Figure 3). These data help in the validation and interpretation of activity inferences.

Step 3. Collect meter & sensor data.

Data from smart meters, electrical appliance plug monitors, and environmental sensors (occupancy, humidity, temperature) are collected to provide real-time information on domestic activity. In the current research, data are collected, stored and analysed *ex post*, but the methodology can also be run in close to real time if data logs can be accessed remotely. In our sample of households, this is currently the case with electricity meter and appliance data, but not gas meter data (which are not used in this study).

Data collection per household was as follows. A smart energy monitor with a current clamp was used to measure the active power load of the whole house at intervals of about 6-8 seconds. Up to 9 individual appliance-specific plug monitors (IAMs) were also installed to measure the active power consumption from the most commonly used electrical appliances, also at about 6 seconds resolution. Plug monitor data were used for validation purposes and to reduce reliance on appliance time diaries (see step 4 below). Occupancy sensors to detect movement were placed in rooms linked to specific activities of interest. Temperature and humidity sensors recording at 1 minute resolution were installed in rooms where activities not directly associated with an electrical device took place, for example, washing using hot water from a gas-fired boiler.

Measurements from all the sensors in the home, including active power, temperature, occupancy, and time-stamp, were wirelessly transmitted to an in-house gateway, and periodically pulled in real time, via the wide area network, by a remote server managed by the research team. Raw measurements were first checked for possible errors and packet drops due to sensor malfunction or communications failure. After pre-processing, the cleaned data were stored and prepared for energy disaggregation and processing.

Step 4. Disaggregate energy and sensor data.

Disaggregation routines using decision tree algorithms are used to identify specific technology-usage patterns (Liao et al. 2014a). The energy-disaggregation algorithm, operating on the pre-processed, time-stamped active power consumption data, performs three routines:

1. *event detection*: detect changes in time-series aggregate load curve due to one or more appliance runs over the base load;
2. *feature extraction*: isolate electrical features, such as edge range, profile between edges, and duration, for each event or appliance run;
3. *classification*: classify the extracted features to the associated electrical appliances.

Data collected from plug monitors are used to build the appliance signature library and train the disaggregation model. Appliance time diaries, self-completed by the households over a period of a few days, are used for validating the disaggregation algorithm and calculating its percentage accuracy. This is then converted into an uncertainty metric used in the activity inferences (see below).

Step 5. Infer time profile of activities.

Not all activities can be inferred from the available real-time data from the smart meters, plug monitors and environmental sensors. Activities that are inferable with current data are shown in the activities ontology without shading (n=5); activities that could be inferred with supplementary data are shown with light grey shading (n=6); activities that cannot be inferred are shown with dark grey shading (n=5) (see Figure 3).

Appliance-usage profiles (see step 4) are used to infer time and energy profiles of activities by associating particular appliance-usage patterns to specific activities. The activity recognition algorithm is based on Dempster-Shafer theory, quantizing the disaggregation uncertainty and consequently providing an indication of inference quality (Liao et al. 2014b). Identifying an activity from the detected events of appliance usage is not straightforward. The main challenges are related to: (1) inaccuracy of low-complexity low-rate energy disaggregation; (2) segmentation problem – whether a concurrent series of appliance usage events belongs to the same activity; (3) recognition problem – classifying the sequence of appliance-usage events to the correct activities. Each activity is identified as a sequence of events involving marker technologies, whose presence indicates that activity certainly occurred, and auxiliary technologies whose presence can only be used to infer occurrence of the mapped activity if other auxiliary or marker technologies are also present. Associated technologies present in the sequence of detected events and linked to an activity, flag that activity as having occurred if there is supporting evidence in the coded ethnography data to support this inference. This is captured in the activities ontology and validated during the final step of the methodology (see below). Type I inferences are made using the smart meter data only, i.e., from appliance signatures but excluding any other environmental information from the ontology in the activity detection algorithm. Type II inferences include both smart meter data as well as temperature and humidity sensor data and potentially also movement data from occupancy sensors. In one household, for example, the 'washing' activity in the bathroom can be detected by a significant change in temperature or humidity readings, as well as the electrical power load associated with the boiler being ignited.

Step 6. Validate activity inferences.

The output of steps 1-5 is a set of time-use profiles for activities that can be reliably inferred or uncertainly inferred from available real-time data. The final step is to validate these inferences using data from activity time diaries self-completed by households. Comparison between inferred activities and recorded activities indicates inference reliability. An example of part of a time diary is shown in Figure 2 (lower right). In our study, comparisons between activity inferences and time diary records took place during a second round of semi-structured household interviews so that reasons for divergence could be identified and discussed. This enabled a further refinement of the activities ontology. For example, technologies in use could be updated, activity<->technology relationships could be re-specified, or an activity's inferrability could be re-designated. It would be possible to compare inferences and time diary records without any further interaction with the household, but this would not help identify reasons for any divergence.

Illustrative Results using Two Case Study Households

The multi-step methodology for making inferences about domestic activities is illustrated using data from two households recruited as part of a trial of smart home technologies involving 20 households in the East Midlands, UK. The trial began in April 2013 and ended in April 2015. The two households are coded anonymously as house 8 and house 10. House 8 is a two person household with a retired couple. House 10 is a four person household with a married couple in their 40s and two children under the age of 10 (one school-age, one pre-school). Data collection was done in two phases. The initial round of household interviews and video ethnography, as well as the house surveys, were carried out in autumn 2013 following recruitment. Smart meters, plug monitors, and sensors were also installed at that time. Real-time data used for the activity inferences were collected in autumn 2014. Appliance and activity time diaries were also self-completed by households during this period.

Results presented here are selective and illustrative only. Their purpose is to demonstrate the activity-inference methodology and how it works in practice. Type I inferences are shown for house 8, i.e., using only electricity meter and appliance data. Type II inferences are shown for house 10, i.e., also using environmental sensor data.

House 8 activity ontology.

The full activities ontology for the kitchen, lounge, dining room and office in house 8 is shown in Figure 4. The ontology for the upstairs bedrooms and bathroom are not shown. Activities are shown in columns, technologies in rows grouped by room. Relationships between technologies and activities are shown in the cells with 'x' denoting marker technologies, '~' denoting auxiliary technologies, and 'o' denoting associated activities (see above for explanation). Activities (shown in columns) are shaded to denote whether they can be inferred from available data (no shading), inferred with uncertainty (light shading), or not inferred (dark shading). Entries in the ontology *in italics* show revisions and corrections following the final validation step 6 of the methodology. 'NA' denotes 'not applicable' so that the cell effectively becomes blank. The original, corrected entry is shown in [ ]. As an example, the desktop computer had originally been identified as possibly associated with 'watching TV', but this association was removed following the validation step (denoted by the cell entry 'NA [~]'). Conversely, the DAB radio in the kitchen had originally been identified as possibly associated with 'cooking' and 'eating', but was also possibly associated with 'laundering' following the validation step. Two activities in their entirety were identified during the validation step as not applicable at all to the household: 'games' using ICTs, and 'caring'. These are shown *in italics* in the activities column headings and are effectively removed from the ontology for this household with the whole column shaded out. Entries in the ontology under location/room shown **in bold** indicate information identified from the video ethnography (with the time stamp included in brackets). These are specifically identified to test the value added of this data resource as it is high cost (once transcribed and analysed) with limited applicability due to research ethics and privacy concerns.

TECHNOLOGIES	**cooking**	**eating**	**washing**	**laundering**	**cleaning**	**sleeping**	**communicating**	**socialising**	**tv**	**radio**	***NA [games]***	**computing**	**hobbies**	***NA [caring]***	**working**	**other**	**Location / Room**
breadmaker	x																kitchen
toaster	x	o															kitchen
omelette maker	x																kitchen
fridge	x																kitchen
crockpot	x																kitchen
microwave	x	o															kitchen
kettle	x	o						o									kitchen
food mixer	x																kitchen
electric oven & hob with extractor fan	x																kitchen
dishwasher	x																kitchen
washing machine				x													kitchen
tumble dryer				x													kitchen
DAB radio	~	~		*~ [ ]*						x							kitchen
gas fire																	lounge
stereo, speakers										x							lounge
VHS VCR								~	x								lounge
PVR (= hard drive?)								~	x								lounge
TV								~	x				o	*NA [~]*			lounge
record player								~		x							lounge
TV								~	x								dining room
DVD player								~	x								dining room
catch-up TV								~	x								dining room
gas fire																	dining room
hostess trolley / kitchenette		x						~									**dining room (t=11.30)**
desktop w/ docking station, monitor							~		*NA [~]*	*NA [~]*	*NA [~]*	~	x	*NA [~]*	NA [~]		office
printer/scanner											*NA [~]*	~	~	*NA [~]*	~		office
shredder															x		office
broadband router							~		~	*NA [~]*	*NA [~]*	~	~	*NA [~]*	~		**office (t=48.00)**
sewing machine					~								~		~		office
cordless phone							x										office

Figure 4. Full activities ontology for house 8.

Various insights can be drawn from the activities ontology for house 8 shown in Figure 4. First, multiple sources of data are necessary to converge on a reliable ontology mapping relationships between technologies and activities in a household. The ontology was constructed initially using interview transcripts and video ethnography on households' use of technology. Successive rounds of data gathering using house surveys, appliance time diaries, activity time diaries, and time diary validation interviews, were all used to expand, revise and finalise the ontology. Second, the structured interviews as part of the validation step added significant value in revising the ontology (entries *in italics*), particularly for ICT-related activities with ambiguous or multiple technology associations. Third, although most cells in the ontology are blank, no column is blank in its entirety except 'other activities', as well as 'caring' and 'games' which were removed following the validation step 6. This means that, in principle and with sufficient data, the full set of 13 activities characterising everyday life in house 8 could be inferred from available real-time data. However, the activities coded as non-inferrable (dark shading) are primarily linked to technologies by indirect association rather than directly. For example, the 'sleeping' activity is associated with use of the radio in the bedroom which marks the 'listening to radio' activity. Additional sensor data could help improve the reliability of these currently non-inferrable activities, but installing more sensors would be costly as well as of potential concern to households. Fourth, it is worth emphasising that the ontology shown in Figure 4 is a cross-section at a point in time. Both activities and technology usage are dynamic elements of everyday life at home. Repeat validation visits to update the ontology would be a necessary step for longitudinal application of the methodology.

House 8 activity inferences.

Figure 5 shows inferences for the 'Daily Routines' activities for house 8 over an hourly time profile from 6am - 12am in a single day (19 September 2014). The height of each column shows the proportion of the hour over which an activity was inferred as occurring. Activities are organised according to whether they are inferrable (no shading), uncertainly inferrable (light shading), or non-inferrable with current data (dark shading). These non-inferrable activities are, by definition, blank.

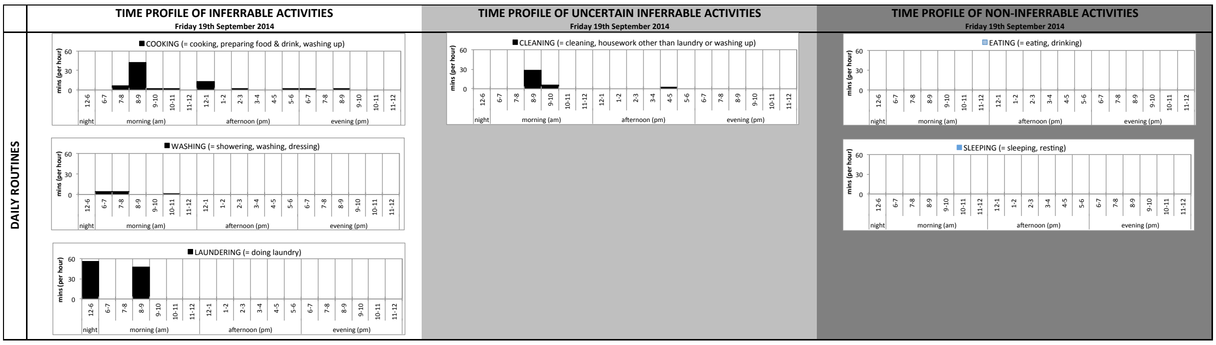

Figure 5. Activity inferences for house 8 (for 'Daily Routine' activities).

Over a seven day period (15-21 September 2014), a total of 6 activities were inferred from a maximum inferrable set of 10. An additional 6 activities were classified as non-inferrable in the ontology (see step 5 of the methodology). Two of the four inferrable or uncertainly inferrable activities - 'cooking' and 'washing' - were detected daily with broadly regular time profiles. 'Laundering' and 'cleaning' were detected on 4 days of the week, with more irregular time profiles. 'Eating' and 'sleeping' were not inferable from the available data, but were recorded in the self-completion time diaries. All six activities are confirmed as part of 'Daily Routines'. 'Watching TV' and 'computing' were also detected daily, but are grouped within the 'Computing & Leisure' category as they are associated with ICTs. Otherwise, no other activity was detected through the inference routines. There were no inferences for 'socialising', 'listening to radio', 'hobbies', and 'other activities' which are all classified as uncertainly-inferrable. All four of these activities were recorded in the time diaries, with 'hobbies' and 'other activities' occupying several hours per day. The time diaries also recorded considerable periods of 'eating', 'sleeping' and 'communicating', all of which are non-inferrable. Overall, the reliability of the inferences is stronger for activities classified as 'Daily Routines' and 'Computing and Leisure', and weaker for the others. Activities classified as uncertainly-inferrable need particular attention in the methodology at step 2 (ontology construction) and step 6 (inference validation).

House 10 activity ontology.

Figure 6 shows part of the ontology for house 10, with the 'Daily Routines' category of activities highlighted against a subset of kitchen appliances. As in Figure 4, entries in the ontology *in italics* show revisions and corrections following the final validation step of the methodology. Two sets of additional information are also included in the ontology. Columns to the left show whether the electrical signature of each appliance is known from an individual appliance-specific plug monitor (IAM) or whether it can be reliably disaggregated from the meter data (NALM). The set of known signals can be expanded if plug monitors are moved between appliances at known times. The appliance time diaries are used for this purpose. Columns to the right summarise known usage patterns of specific appliances from the qualitative data. Entries **in bold** are from the video ethnography (and include time stamps). This additional information is used in the inferences validation step. Discrepancies between inferences and general usage patterns are identified and explored through semi-structured interviews. Revisions and additions following the validation step are shown ***in bold italics***.

House 10 activity inferences.

Figure 7 compares activity inferences with time diary records for the 'Interacting' and 'Computing & Leisure' categories of activity. The top panel shows inferences; the bottom panel shows time diaries. Correspondence is fairly good. There are small discrepancies in the 'computing' and 'listening to radio' activities, either missed by the inferences, or inappropriately recorded in the time diaries. Some of the activity inferences were for longer durations than the self-recorded activities in the time diaries. Multi-tasking was the most common explanation discussed during the validation visit. Particularly on weekdays would be doing several activities concurrently, e.g., ‘cooking’, ‘laundering’, ‘cleaning’, ‘listening to radio’, ‘watching TV’. Only the more salient of these activities would be recorded in the time diaries. Similarly, some activities comprise active, discrete events during a longer activity period. For example, ‘laundering’ involves active periods of putting on and taking out a load of laundry, as well as a long passive period during which the washing machine is working. Only the active periods would be recorded in the time diaries.

Another consequence of multi-tasking was a large number of indirect or secondary associations between technologies and activities. This led to many additions to the activities ontology for ‘~ auxiliary technology’. This was particularly the case for Tuesdays which were noted as days of the “*cleaning blitz*”. As examples, the iron and tumble dryer are ‘x marker technologies’ for the ‘laundering’ activity, but following the validation visit, a further set of ‘~ auxiliary technologies’ were added to the ontology for ‘laundering’: food processor and slow cooker (as ‘cooking’ tended to occur while the washing machines was on); vacuum cleaner (ditto ‘cleaning’); TV and programmable video recorder (ditto ‘watching TV’). Household routines strongly characterised by multi-tasking clearly pose a problem for inference validation.

TECHNOLOGIES	**Signature Availability**	**Appliance Measurability**	**cooking**	**eating**	**washing**	**laundering**	**cleaning**	**sleeping**	**Location / Room**	**Fixed / Mobile**	**When Used**	**Frequency of Use**
Dishwasher	IAM	*measurable*	x			*[ ] ~*	*[ ] ~*		kitchen	(fixed)	after dinner	most evenings - definitely once a d
Washing machine	IAM	*measurable*	*[ ] ~*			x			kitchen	fixed		**at least once a day (t=1.00)**
Tumble dryer	NALM	*measurable*	*[ ] ~*			x	***[ ] ~***					
Radio	potentially NALM	*if plug moved*	~	~			***[ ] ~***		kitchen	(fixed)	throughout day - esp. mornings	
iPod / Base docking station			~	~					kitchen	fixed		**most days (t=2.00)**
Iron	potentially NALM	*if plug moved*				x	***[ ] ~***		kitchen		AM	Tuesdays
Sandwich maker		*if plug moved*	x	o								As needed
Breadmaker	IAM	*measurable*	x	o					kitchen			
Kettle	NALM	*measurable*	x	o					kitchen	fixed	every day	regular intervals throughout day
Toaster	NALM	*measurable*	x	o					kitchen	fixed	***Breakfast***	***2/3 times a week***

Figure 6. Part of the activities ontology for house 10.

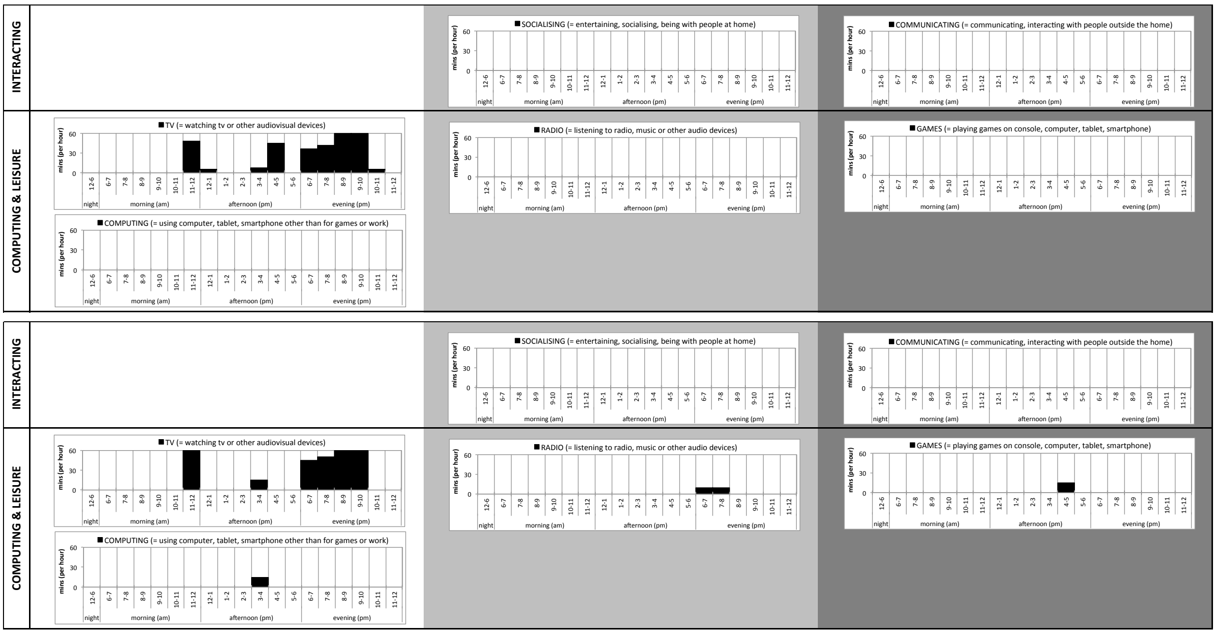

Figure 7. Activities from inference methodology (top panel) and self-recorded time diaries (bottom panel) in House 10 for Monday December 1st 2014.

Discussion & conclusions

The methodology set out and demonstrated in this paper can be used to make reliable inferences about a set of activities that comprehensively characterises domestic life. The methodology has several important advantages. First, the use of multiple data sources, both quantitative and qualitative, improves the scope and robustness of the activities ontology. Household interviews, house and appliance surveys, and time diaries of both appliance use and activities, are all integral to the methodology. Second, the post-inference validation step improves confidence in both the activities ontology and resulting inferences. The ontology can be revised and corrected prior to a final iteration of the inference routines on the same underlying data. Third, household-level time-use profiles can be compared with national time-use statistics to identify variability or segment households according to their everyday activities. Fourth, the validation visits provided an opportunity to talk through the activity inferences with house 8 and 10. These discussions confirmed the benefits of an activity-centric approach for providing feedback on domestic life. Particularly in house 8, activities resonated as a meaningful way to reflect on everyday domestic life. Fifth, an activity-centric lens on domestic life can be applied to the challenge of feeding back real-time energy use data to households in a way that is salient and meaningful to households' lived experiences. The methodology as demonstrated generates hourly time-use profiles of different activities. The energy intensity of each activity (kWh/minutes) can be used to convert time-use profiles into energy data. Alternatively the disaggregated meter and plug monitor data can be used directly to quantify energy use per activity per time period. Once the ontology and initial set of inferences are validated, this could potentially be done in real time rather than *ex post* as demonstrated in this paper. The methodology therefore significantly extends the current state of the art with both household energy feedback and service-based accounts of domestic life.

The methodology also has certain constraints and resource limitations. First, the use of mixed methods, as well as quantitative and qualitative data, requires a multi-disciplinary research team with frequent interactions both within the team and between the team and households. This has implications for researcher time and skills, and incentives to support households' ongoing commitment to the research. Second, the household interviews and time diaries allow a comprehensive set of activities to be characterised and included in the time diaries. However, the real-time data are energy-centric, so the activities that can be inferred reliably are energy-using. However, it is possible to infer non energy-using activities if these activities can be mapped with additional sensors, e.g., sleeping could be detected with light sensors. Inferences on ICT-related activities are also uncertain due to the multiple activities potentially associated with any given device. These uncertainties are further exacerbated with mobile, battery-powered devices (smart phones, tablets, laptops). These could be inferred if video sensor data or software logging on mobile devices could be used. However, these are intrusive and of concern to household occupants, particularly with respect to privacy and security. Third, neither heating and lighting are activities per se, but as energy-intensive services they can not be omitted from activity-centric accounts of everyday life generated by real-time energy data. It is difficult to apportion energy used for heating and lighting across the activities they enable. Including heating and lighting as separate energy services in addition to the set of inferred activities is the simplest way to avoid missing energy data.

This paper has demonstrated the potential for making reliable inferences about a set of activities that comprehensively characterise everyday life at home from the households' perspective. This activity-centric approach provides a potential lens for feeding back energy-related information to households in a way that is meaningful, salient, and useful. Further research is needed to demonstrate the methodology at scale, with reduced data requirements, but this paper demonstrates proof of concept.

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