Chapter 4
Routines and Energy Intensity of Activities in the Smart Home

L. Stankovic, V. Stankovic, J. Liao and Charlie Wilson

Abstract The instrumental view of smart homes and their users is premised on active management of energy demand contributing to energy system objectives. In this chapter we explore a novel way of using data from smart home technologies (SHTs) to link energy consumption in homes to daily activities. We use activities as a descriptive term for the common ways households spend their time at home. These activities, such as cooking or laundering, are meaningful to households' own lived experience. We set out a novel method for disaggregating a household's electricity consumption down to the appliance level allowing us to make inferences about the activities occurring in the home in any given time period. We apply this method to analyse the pattern of activities over the course of one month in 10 of the homes participating in the SHT field trial described in Chap. 1. We show how both the energy intensity and temporal routines of different activities vary both within and between households. Our method also clearly reveals the complexities of everyday life at home which shapes the domestication of SHTs.

4.1 Introduction and Key Questions

The analytical framework introduced in Chap. 2 identifies research themes on the 'home as a complex place' characterised by both routine and regularity, as well as variability and vicissitude. Against this backdrop, domestic energy use is the largely invisible consequence of activities taking place within the home (Gram-Hanssen 2014; Katzeff and Wangel 2015). Activities such as cooking, washing, listening to music or playing computer games are more consistent with households' own experiences of life at home. Activities are a simple descriptive term for these common ways in which households spend their time, and are used in time-use statistics collected by national statistical agencies to characterise the everyday life of households (ONS 2000a). From an energy perspective, activities are also a more stable constituent of domestic life whereas appliances may be commonly replaced or retrofitted (Schwartz et al. 2014).

In this chapter, we ask three important questions on the linkages between energy use and domestic activities in smart homes:

Q1   How can data from SHTs be mapped onto domestic activities?
Q2   What is the energy intensity and routineness of different activities?
Q3   How do activity patterns vary within and between households?

To answer these questions, we present a novel data-processing methodology using both quantitative and qualitative data to make inferences about electricity-consuming activities in the home. We apply this method to look in-depth at the time profile and energy intensity of a set of 10 activities that constitute everyday life in a smart home.

4.2   Method

Smart meter data provide real-time information on aggregate energy consumption in homes. Disaggregating smart meter data via intrusive or non-intrusive means helps understand how appliances consume electricity in individual households (Zeifman and Roth 2011). Load disaggregation effectively breaks the electricity consumption of a household down to the individual appliances that contribute to the total load at any point in time (An electrical load is a component of an electrical circuit that consumes power, e.g., an appliance or light). Monitoring consumption at the plug level using individual appliance monitors (IAMs) is becoming affordable, but it is also intrusive particularly if monitoring the 30 or more appliances in a typical home. An alternative is to use non-intrusive approaches based on algorithms to infer load profiles from smart meter data. Non-intrusive appliance load monitoring (NILM) disaggregates a household's total electricity consumption down to specific appliances (Zeifman and Roth 2011; Zoha et al. 2012). NILM effectively creates virtual power sensors at each appliance using software tools alone. In principle, NILM using smart meter data can disaggregate which appliances were used, when they were used, for how long, and with what consequence for electricity consumption.

In this chapter we present a novel methodology to infer the occurrence and associated electricity consumption of domestic activities using smart meter data. The methodology is based on an activity recognition algorithm that identifies appliance usage events: (i) by directly monitoring appliances via individual appliance monitors (IAMs); (ii) by using non-intrusive appliance load monitoring (NILM); and (iii) by defining activity ontologies using qualitative data from interviews and physical home surveys.

Our methodology consists of five steps which are applied separately for each home analysed:

1. *Activity selection*: Select activities relevant to a specific home from a set of 10 activities that characterise domestic life.

2. *Data collection*: Collect real-time electricity data from smart electricity meters and IAMs. Collect data on home and household characteristics including routines and appliance usage patterns.
3. *Load disaggregation*: Disaggregate electricity data using NILM to identify operation of all appliances that are not monitored directly by IAMs.
4. *Activities ontology*: Formally map relationships between activities and appliances to build an 'activities ontology'.
5. *Activity inferences*: Use activities ontology and disaggregated electricity data to make inferences about when and for how long activities are occurring, and with what consequence for electricity consumption.

We summarise the key features of each step below. For a more detailed explanation of the methodology, see: Liao et al. (2014a), Stankovic et al. (2015).

Activity selection

We identified a comprehensive set of activities based on the UK's Office of National Statistics (ONS) double-digit (disaggregated) codes for time-use studies (ONS 2000a, b). We excluded two types of activity: (i) activities that do not take place within the home (e.g., travel), or only take place within the home under specific circumstances (e.g., volunteering, sport); (ii) activities that are not clearly associated with energy-using appliances (e.g., sleeping, eating). We aggregated the remaining ONS double-digit codes into a set of 10 activities which are linked to specific energy-using appliances and which constitute the majority of life at home. These are summarised in Table 4.1; for further details, see Wilson et al. (2015).

Table 4.1 Activities and common marker technologies for a set of 10 activities

	Activity	Common marker appliances	Detection method
Daily routines	Cooking	Kettle, microwave, oven, toaster, dishwasher, electric cooker	NILM
	Washing	Electric shower, hair dryer, hair straightener	NILM
	Laundering	Washing machine, tumble dryer	NILM
	Cleaning	Vacuum cleaner, steam mop	NILM
Leisure and computing	Watching TV	Television, DVD player, recorder, set top box	NILM, IAM
	Listening to radio	CD player, hi-fi	IAM
	Games	Gaming console	IAM
	Computing	PC, printer, scanner	NILM, IAM
	Hobbies	Exercise machine, electric drill, sewing machine	NILM
	Socialising	[*Indirect associations through linked activities*]	N/a

Our set of 10 activities can be distinguished broadly as daily routines (cooking, washing, laundering, cleaning) or as leisure and computing (watching TV, listening to radio or music, playing computer games, all other computing, hobbies). Socialising is an activity that constitutes daily life but does not directly consume energy. However, it can be inferred indirectly from linked activities, e.g., listening to music (Table 4.1).

Data collection

We collected a combination of quantitative and qualitative data in each home being analysed.

Quantitative data comprise aggregate and individual appliance active power in Watts (W) sampled every eight seconds, similar to the specifications of smart meters being rolled out nationally in the UK (DECC 2014). Up to nine IAMs were used in each home to collect data on individual appliances. The electrical consumption of the remaining appliances were all obtained via load disaggregation using NILM (Liao et al. 2014a). All electricity data used in this study are publicly available (see Table 1.2).

Qualitative data comprise: (1) appliance surveys; (2) semi-structured household interviews on activities; (3) video ethnography on technology ownership and usage. The appliance surveys are to help identify unknown signatures obtained during NILM. The qualitative interview and video ethnography data procedures are explained further in Chap. 5; see also Wilson et al. (2015). We used the interview and video data to identify domestic routines and appliance usage that helped us map relationships between activities and technologies for each household (see below).

Load disaggregation

Information on when different appliances were running was either measured by IAMs or inferred from the aggregate readings via NILM. We used a mix of physical sensors (IAMs) and virtual sensors (via NILM) for two reasons. First, monitoring every single appliance in a home via a physical sensor is expensive and unpractical. As a result, we only used up to nine IAMs in each home which kept acquisition, processing and storage cost and complexity manageable. Second, NILM introduces inference uncertainty. The performance or accuracy of NILM is dependent on the smart meter data time-resolution, an up-to-date repository of appliance load signatures, algorithmic complexity, and robustness of the algorithm to unknown signatures detected in any given home. As a result, we did not rely exclusively on NILM.

The output of the disaggregation process is detailed information about each appliance use or event, detected within the chosen period of disaggregation. Specifically, this comprises the time when the appliance was switched on and when it was switched off, the duration of that event, appliance label, average effective power (W) and the total consumption (in kWh) of the appliance during that event. Our disaggregation algorithm accurately detects as many events as possible to account for electricity-using appliances which contribute to the aggregate load at any given point in time.

Activities ontology

The load disaggregation provides a list of specific appliances used together with their time of use. This information is related to particular activities using an 'activities ontology' specific to each home. An activity ontology maps out all known relationships between activities and the appliances used in those activities. The purpose of the ontology is to link measurable information on appliances to the set of activities characterising everyday life at home.

Mappings between appliances and activities are non-exclusive, i.e., one activity can be mapped to one or more appliance, and vice versa. Any given appliance can *definitely, possibly,* or *indirectly* indicate that an activity is occurring. These are distinguished in the ontology through three corresponding codes: *marker appliance, auxiliary appliance,* and *associated activity*.

Marker appliances are appliances whose use tells us when an activity is definitely occurring. For example, a washing machine is one of the marker appliances for the laundering activity. Table 4.1 shows a general mapping of common marker appliances for all activities (except socialising) and how the electrical loads of these marker appliances are measured quantitatively. Disaggregation cannot capture the use of devices that are highly mobile or that operate on battery power (either permanently or while not plugged in). As a result, mobile or battery-powered devices are not used as marker technologies in the activities ontology.

Appliances used for several different activities cannot be used unambiguously for making activity inferences. Whereas marker appliances identify when an activity is definitely going on, *auxiliary appliances* indicate that an activity is possibly going on. For example, a householder could use a PC (marker appliance for the computing activity) for the 'listening to radio' activity (which is defined as listening to any audio regardless of the device used).

An *associated activity* refers to the use of an appliance that is a marker for one activity which is in turn concurrent with or linked to a second activity. For example, a hi-fi is a marker appliance for 'listening to radio' but might also indicate the 'socialising' activity, which is therefore an associated activity. 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. To avoid the risk of inference errors, ICT-based activities could be collapsed into a higher order 'all ICT-related' activities but this is less useful as a descriptive characterisation of domestic life.

Activity inferences

The output of the activity inference procedure is a set of activities, together with their start times and end times to estimate duration. With the disaggregated electrical consumption obtained from IAM or NILM, we can then determine the electrical load associated with each activity from the temporal associations of appliances which form one activity event.

Our methodology can under-predict activity time use because some appliances may be off during part of the activity, e.g., when loading the washing machine

during the laundering activity, or preparing meat or vegetables for the cooking activity. On the other hand, our methodology can also over-predict the duration of an activity if marker or auxiliary appliances are on for prolonged periods beyond the duration of an activity, e.g., a radio or TV left on all day, regardless of whether a householder is actually listening to the radio or watching TV. Making inferences solely from appliance usage is not reliable as a sole basis for inferring the time profile of activities. However, given that the disaggregated loads from specific appliances are known and can then be linked to activities based on the ontologies, the energy intensity of domestic activities can be reliably calculated.

Uncertainties in activity inferences

The disaggregation introduces some uncertainty due to IAM sensor malfunctions or NILM misclassification if two appliances have similar active power signatures. Uncertainty is also introduced by the stochastic nature of human behaviour as there are many ways an activity can be carried out. As an example, certain activities may use different subsets of appliances within the defined ontology at different times. This is a common problem in domestic activity recognition studies. These two uncertainties are termed *disaggregation uncertainty* and *context uncertainty* respectively (Liao et al. 2014b).

We classified each of our activity inferences at one of five levels of uncertainty:

1. *Non-inferable*: Activities associated with non-detectable appliances which cannot be monitored (e.g., a battery-operated appliance like a portable radio) or with mobile, chargeable devices (e.g., laptops or tablets).
2. *Possibly inferable*: Activities associated with non-detectable appliances because additional quantitative and/or qualitative data is required for disaggregation. An example is the washing activity using gas water heating which could be monitored by additional temperature or humidity sensors.
3. *Inferable with uncertainty*: Activities associated with appliances whose signatures have not been verified but can still be detected via disaggregation, or medium-powered appliances whose signatures can 'get lost' in the aggregate data. An example is the cooking activity which is associated with a large range of different appliances used at different times and for which all signatures cannot be verified.
4. *Partially inferable*: Activities associated with gas as well as electricity consumption (e.g., the washing activity associated with both an electric shower and gas-based domestic hot water) or with appliances which cannot be disaggregated due to low loads (e.g., the listening to radio activity which can be partly detected if there is an IAM attached to at least one associated appliance like a CD player).
5. *Inferable with certainty*: Activities associated with appliances detected reliably via NILM and/or IAMs. Note that the NILM appliances may incur marginal disaggregation error, but usually no more than 10% (Liao et al. 2014a).

4.3   Data

We applied our methodology to make inferences about 10 activities over 24 h daily cycles for each day of the month of October 2014. We selected this period as it was not during the summer (when households are more likely to be outside) and also not during school holidays or festive periods (when domestic activities in households may follow different routines).

   We used data from a sample of 10 households participating in the SHT field trial (see Chap. 1). We selected the households to ensure variation in household compositions:

- pensioner couples (Houses 3, 4 and 8)
- families of four with two young children (Houses 2 and 10)
- families of four with two teenage children (Houses 5, 19, 21)
- other household compositions (Houses 17, 20).

For further details of the ages and occupations of household members in each of these houses, see Table 1.3.
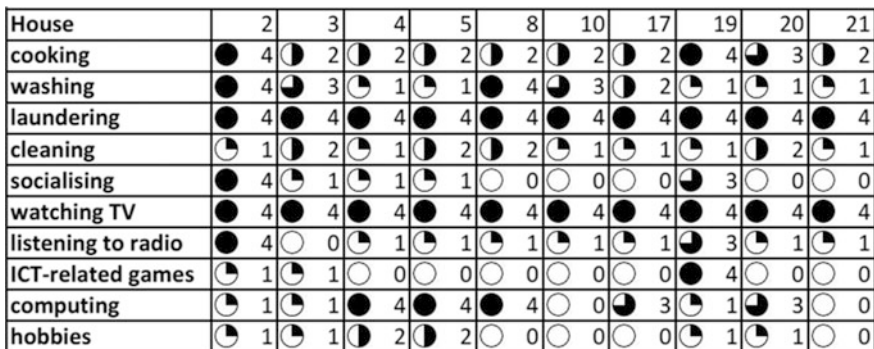
   For each household, an activities ontology was built to map activities which could be inferred with the appliances associated with each activity. Using House 17 as an example, Table 4.2 shows which activities can be inferred from the collected data, whether our inference algorithm can measure the duration of the activity as well as electricity use, and which appliances were related to activities or other electricity consumption. The appliance information was obtained through a combination of the appliance survey, qualitative data, and NILM. Not all appliances were reported in the appliance survey because they were either unused during the survey or they were not present in the house at the time of the survey.

   We also estimated non-activity based electricity consumption, distinguishing cold appliances, electrical heating (if applicable), base load, and a residual which includes lighting (Table 4.2). The residual indicates how much of total electricity consumption we can neither disaggregate nor indirectly account for. 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 (De Lauretis et al. 2016). We chose instead to account for heating and lighting separately to maintain only direct linkages between activities and energy consumption.

   Figure 4.1 shows which of the full set of 10 activities could be detected in each of the 10 households in our sample, together with associated uncertainties. As an example, we could detect watching TV in all households with high certainty (coded 4) because of marker appliances (e.g., TVs) monitored by plug monitors. Similarly, we could detect laundering in all households with high certainty because marker appliances (e.g., washing machines, dryers) have well defined signatures for NILM. Some activities were inferable through their associations with a different activity (e.g., socialising was inferred indirectly from listening to radio if the two were associated in the ontology for that household).

Table 4.2 Activity inferences from detected appliances in House 17 (Notes: Uncertainty for each activity is coded from 0 (non-inferable) to 4 (inferable with certainty); see text for details)

Activities and other types of electricity consumption		Inferences			Appliances
		Time use	Electricity use	Uncertainty	
Activity-related	Cooking	Yes	Yes	2	Kettle, microwave, coffee maker, toaster, blender, electric cooker, sandwich maker
	Washing	Yes	Yes	2	Electric shower, hair straightener
	Laundering	Yes	Yes	4	Washing machine, tumble dryer
	Cleaning	No	No	1	N/a
	Watching TV	Yes	Yes	4	Television, DVD, set-top box, speakers
	Listening to radio	No	No	1	N/a
	Games	No	No	0	N/a
	Computing	Yes	Yes	3	Desktop computer
	Hobbies	No	No	0	N/a
	Socialising	No	N/a	0	N/a
Other	Cold appliances	N/a	Yes		Fridge-freezer, two freezers
	Electric heating	N/a	Yes		Electric heater
	Base load	N/a	Yes		N/a
	Residual	N/a	Yes		N/a

Fig. 4.1 Uncertainties in activity inferences (Notes: Unshaded 0 = *non-inferable*; quarter-shaded 1 = *possibly inferable*; half-shaded 2 = *inferable with uncertainty*; three-quarters shaded 3 = *partially inferable*; fully shaded 4 = *inferable with certainty*)

## 4.4   Results: Time Profile of Activity-Based Electricity Demand

To illustrate our methodology, we generated the time profile of electricity demand for three daily activities (cooking, laundering and washing) and one leisure activity (watching TV) in the 10 households in our sample, broken down into weekday and weekend profiles (Fig. 4.2). The time profiles were averaged over the 23 weekdays and eight weekend days in October 2014.

Cooking occurs throughout the day across all households, but shows clear peak hours for breakfast, lunch and particularly dinner. However in most households cooking is less structured during weekends, occurring more consistently throughout the day with less pronounced peaks. Watching TV has a similar time profile to cooking, with evening peaks which are more pronounced during weekends. Washing has a very pronounced peak during weekday mornings. Although morning peaks are also evident during weekends, washing becomes more spread out through the day. Laundering also tends to peak mid-morning, but is spread throughout the day including into the evening. The time profile of laundering varies markedly from household to household, but is fairly consistent from weekdays to weekends.
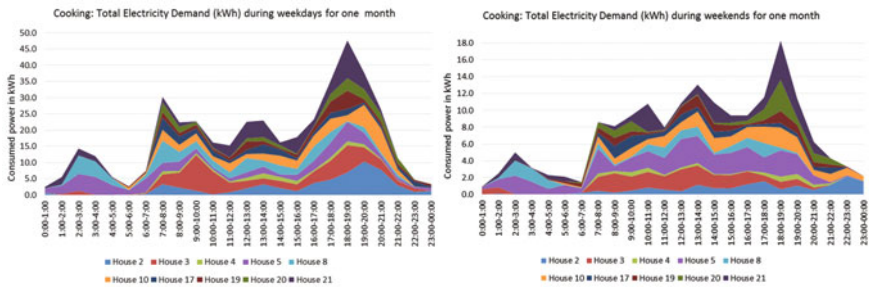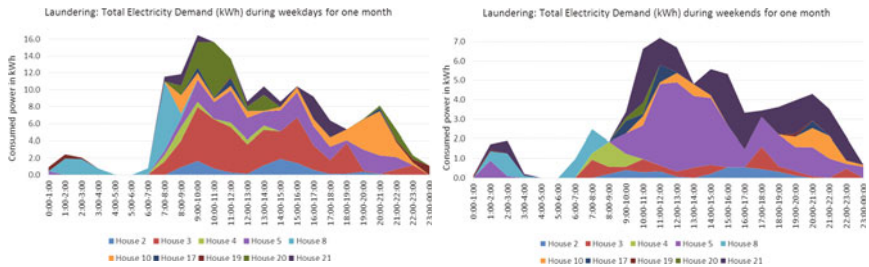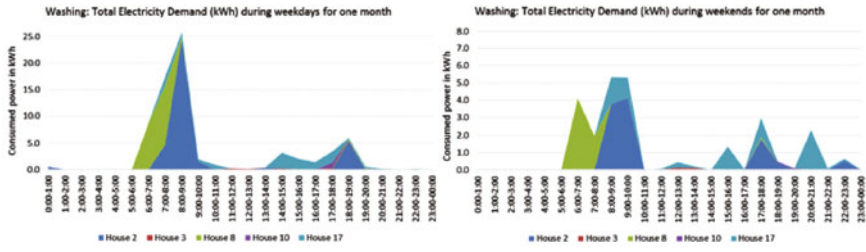

Fig. 4.2 Activity-based electricity demand during weekdays and weekends (Notes: Left panels show weekdays; Right panels show weekends; Demand was calculated for all 10 households for all activities shown, except washing which was calculated for five households)
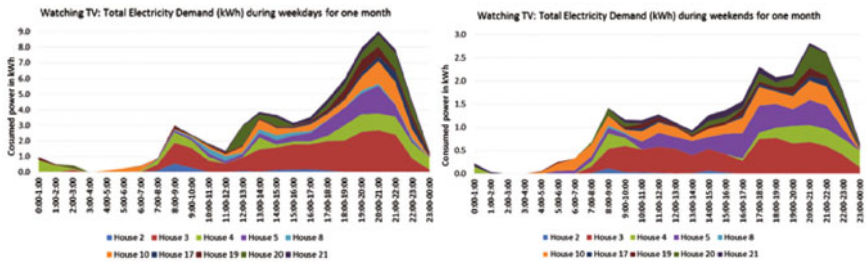
Washing

Watching TV

Fig. 4.2 (continued)

4.5 Results: Energy Intensity of Domestic Activities

To make standardised comparisons of activity-based electricity consumption within and across households, we defined an energy intensity metric to quantify the relative contribution of activities to total household energy consumption. We refer to this as the *energy intensity* or EI_a of Activity a which is calculated as the percentage of total electricity consumption attributable to Activity a during any given time period T. An energy intensity of 0% [i.e., $EI_a(T) = 0$] means that Activity a did not occur during time period T, whereas an energy intensity of 100% [i.e., $EI_a(T) = 1$] means that the entire household's electricity consumption over time period T is attributable to Activity a.

Within a single household

We applied this energy intensity metric to analyse the time profile of electricity consumption of particular activities within a single household. Figure 4.3 shows data from House 5 during October 2014. House 5 is a four person household with two adults and two children in their early teens. Inferable activities account for 40% of the total monthly electricity consumption, with cooking, computing and
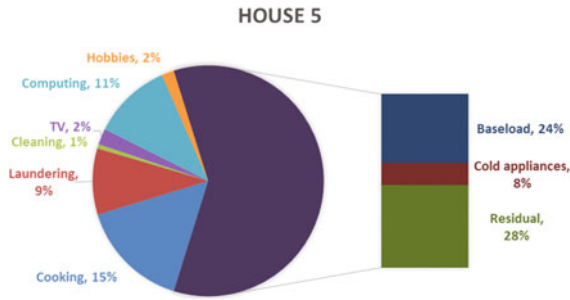
Fig. 4.3 Energy intensity of six activities in house 5 over a one month period

laundering the most energy-intensive activities ($EI_{Cooking}$ = 15%, $EI_{Computing}$ = 11%, $EI_{Laundering}$ = 9%). Over the whole month, the residual load (including lighting) unaccounted for by activities, baseload or cold appliances is 28% of total consumption.
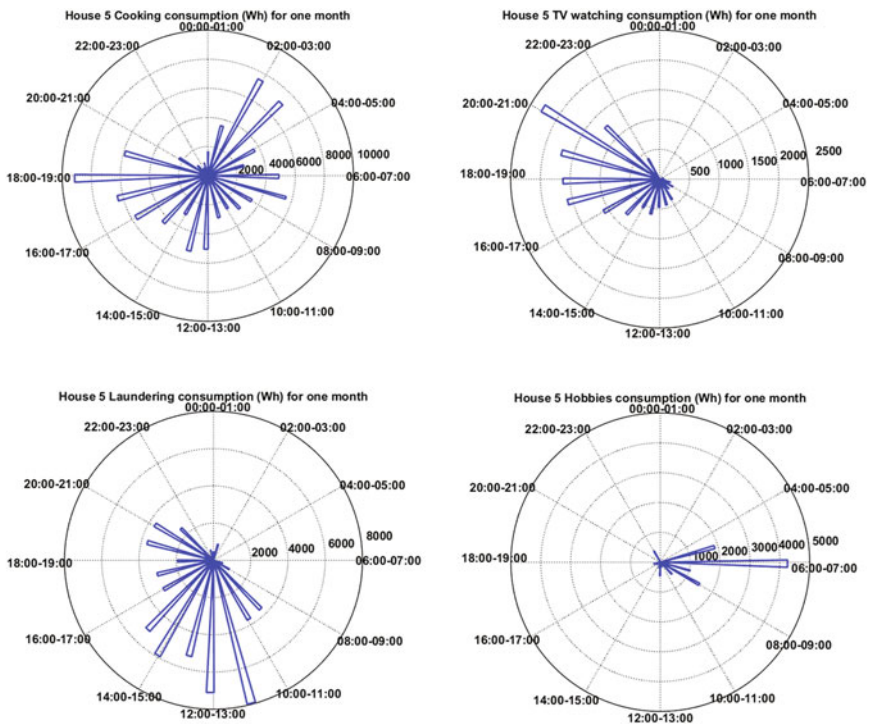

Fig. 4.4 The time profile of electricity consumption per activity in house 5 (Notes: Each hourly bin shows the total electricity consumption (Wh) over a month)

Although Fig. 4.3 is useful for comparing the relative energy intensities of different activities overall, it does not show their distribution over time. Figure 4.4 uses rose plots to illustrate the time profile of total monthly electricity consumption for four activities across each hourly time period summed over a month. Note that the scales of the radial axes (Wh) vary for each plot. Figure 4.4 clearly indicates peaks during particular time periods. For example, cooking occurs throughout the day, but with a clear evening peak from 6–7 pm. The distinctive overnight dishwasher usage in the cooking activity is shown as another peak from 2–4 am. Laundering is more spread out through the day, whereas hobbies (use of a treadmill) is limited to the early mornings. Watching TV is mainly an evening activity.

Between households

Our activity-inference methodology can be used to link electricity consumption to a common set of activities across multiple households. Table 4.3 shows the energy intensity of all activities inferred across our sample of 10 households. The energy intensity of inferable activities ranges from 13 to 41% across households over the whole month. Of all the activities which are generally inferable across households from available electricity data, cooking has the highest energy intensity with an average $EI_{cooking} = 16\%$. Laundering and washing are the next most energy intensive activities. Note that washing could only be inferred in a subset of households which did not also use gas for hot water.

Table 4.3 Energy intensity of all inferable activities in 10 houses over a one month period (Notes: Cells with no entry indicate no quantitative and/or qualitative data to make inferences)

House / *Activities*	2	3	4	5	8	10	17	19	20	21
cooking	21%	20%	6%	15%	16%	17%	12%	15%	13%	23%
washing	14%	<1%			6%	<1%	7%			
laundering	4%	12%	3%	9%	4%	6%	2%	1%	6%	9%
cleaning		1%		1%	1%				1%	
watching TV	1%	7%	2%	2%	1%	3%	1%	2%	3%	1%
listening to radio	<1%							<1%		
ICT-related games								1%		
computing			2%	11%	2%		5%		1%	
hobbies			1%	2%						
socialising	<1%							<1%		
total activity-based electricity use	**40%**	**41%**	**13%**	**40%**	**30%**	**26%**	**26%**	**20%**	**24%**	**34%**
base load	17%	18%	22%	24%	15%	20%	21%	41%	30%	28%
cold appliances	9%	18%	31%	8%	6%	9%	22%	16%	23%	9%
electrical heater					1%	3%	13%			
residual (inc. lighting)	34%	23%	33%	28%	47%	42%	18%	23%	23%	30%

Other (non-activity) electricity consumption comprises cold appliances, base load, electrical heating, and a residual, including lighting and charging of portable devices or low-powered devices, which we could not disaggregate. This residual is 18–48% of total electricity use. Other studies have shown that lighting in the UK uses an average of 16% of a household's total consumption (Bertoldi and Atanasiu 2006).

4.6   Results: Routines and Rhythms in Domestic Activities

Our energy intensity metric, $EI_a(T)$, allows energy-using activities to be compared on a like-for-like basis between time periods within a household, or within time periods between households. However, it does not take into account how consistently activities occur during any given time period. As an example, activities may have similar energy intensities over a one month period if they occur daily and regularly for short periods (e.g., cooking), or for longer periods during only a few days (e.g., laundering).

We defined a routine metric as an indicator of how consistently activities occur during any time period. Our routine metric captures variability in each activity's duration in terms of both frequency during a given time period (i.e., how often the activity occurs) and consistency (i.e., whether the activity regularly occurs in the same timeslot). To measure routine occurrence we use the coefficient of variation, $R_a(t, T)$, also known as the relative standard deviation. We calculate $R_a(t, T)$ as the ratio of the standard deviation to the mean of the energy consumed by Activity a during time period T for each timeslot t. Larger values of the routine metric, $R_a(t, T)$, indicate that an activity occurs less frequently and/or occurs irregularly during timeslot t. Smaller values of $R_a(t, T)$ indicate that an activity occurs frequently with similar durations during timeslot t. No values or gaps in $R_a(t, T)$ indicate that an activity never takes place during that particular timeslot t.

Within a single household

Figure 4.5 shows the routine metric, $R_a(t, T)$, for House 5 for each hourly timeslot t in a day, averaged over a whole month. Computing has a very low R value because the desktop computer is switched on 24/7 so that this activity is both frequently and consistently occurring over the month. Watching TV occurs consistently and every day in the evenings (low R values) and inconsistently at other times of the day (high R values). Cooking happens consistently every day during breakfast and dinner times, and overnight (dishwashing), but is inconsistent at other times of the day. Laundering does not happen every day (infrequent) and also occurs at different times during the day (inconsistent). Hobbies take place consistently from 6–8 am, but do not occur every day (infrequent). Hobbies are also inconsistent at other times of the day.
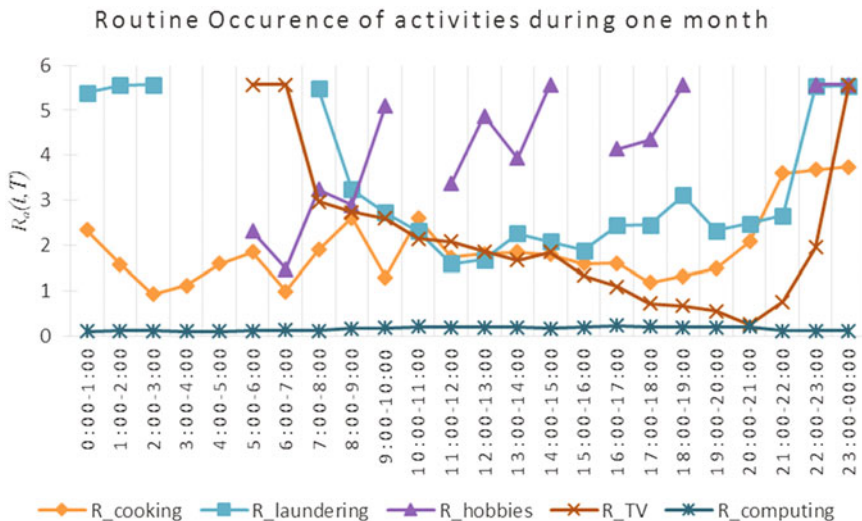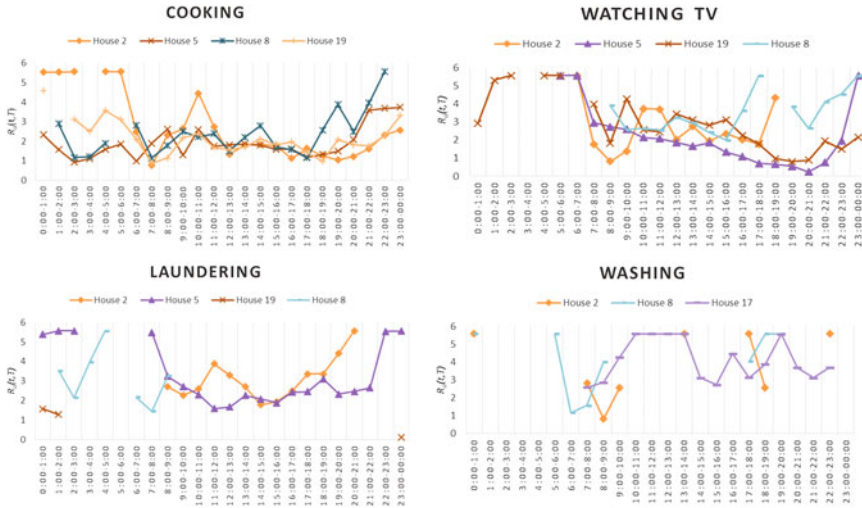
Fig. 4.5 Routine in the time profile of activities in house 5 during hourly timeslots over a one month period (Notes: Routine is measured using the routine metric, $R_a(t, T)$; High values of $R_a(t, T)$ indicate no routine during that timeslot (infrequent and/or inconsistent activities); Low values of $R_a(t, T)$ indicate routine during that timeslot (frequent and/or consistent); Gap in values of $R_a(t, T)$ indicates no activities during that timeslot)

Between households

In order to understand variability across households for each activity, Fig. 4.6 shows the $R_a(t, T)$ for for each hourly timeslot t over a one month period T for a sub-sample of households which represent the main household compositions. The plots have the same interpretation as Fig. 4.5 which shows multiple activities for a single household, but Fig. 4.6 shows a single activity across multiple households. As before, small $R_a(t, T)$ values indicate more routine occurrence; large $R_a(t, T)$ indicates less routine occurrence. Convergent or clustered $R_a(t, T)$ values indicate similar routines across households; divergent $R_a(t, T)$ indicates different routines across households.

Cooking generally has a clear routine time profile for breakfast, lunch and dinner timeslots across all households. Houses 5 and 19 watch TV with increasing consistency from early afternoon to evening. Houses 8 and 19 are distinctive in laundering overnight and never after 8 am. Both households are on the Economy7 tariff which has a lower off-peak cost overnight from 10 pm to 8 am (Murray et al. 2015). Houses 2 and 8 are very consistent in their washing routine in the morning, unlike House 17 which has large variability throughout the day.

Fig. 4.6 Routine in the time profile of cooking, watching TV, laundering and washing in four houses during hourly timeslots over a one month period (Notes: Routine is measured using the routine metric, $R_a(t, T)$; High values of $R_a(t, T)$ indicate no routine during that timeslot (infrequent and/or inconsistent activities); Low values of $R_a(t, T)$ indicate routine during that timeslot (frequent and/or consistent); Gap in values of $R_a(t, T)$ indicates no activities during that timeslot)

4.7   Results: Activities in Households with Similar Composition

To test the influence of household composition on the occurrence and time profile of domestic activities, we compared the energy intensity and routine of activities within households of similar compositions. We used three distinct types of household within our sample: families of four with two small children (Houses 2 and 10); families of four with two teenage children (Houses 5, 19 and 21); and pensioner couples (Houses 3, 4 and 8).

Table 4.4 shows that there is no systematic association between energy intensity and routine on the one hand, and household composition on the other. Even if energy intensities of the activities are similar, the routines for these activities can be very different. For example, of the four member households with two teenage children, House 19 has a very different $EI_{laundering}$ and $R_{laundering}$ to Houses 5 and 21. This could be due to their use of the overnight Economy7 tariff. Conversely House 21 has the least routine laundering shown by the high value of $R_{laundering}$.

Table 4.4 Energy intensity and routine of cooking, laundering and watching TV activities across households of similar composition (Notes: Energy intensity is measured using the metric, $EI_a(T)$, and routine is measured using the routine metric, $R_a(t, T)$, with t as hourly timeslots and T as the one month measurement period; High values of $EI_a(T)$ indicate large % of total electricity consumption (and vice versa for low values); High values of $R_a(t, T)$ indicate no routine during that timeslot (and vice versa for low values))

Household composition	House	Total monthly electricity use (kWh)	Energy intensity			Routine		
			$EI_{cooking}$ (%)	$EI_{laundering}$ (%)	$EI_{watching\ TV}$ (%)	$R_{cooking}$ (%)	$R_{laundering}$ (%)	$R_{watching\ TV}$ (%)
Families of four with two small children	2	338	21	4	1	2.61	1.68	1.43
	10	417	17	6	3	1.62	2.18	1.49
Families of four with two teenage children	5	636	15	9	2	1.93	2.76	1.75
	19	248	15	1	2	2.09	1.04	2.70
	21	333	23	9	1	2.62	3.65	1.99
A pensioner couple	3	450	20	12	7	3.05	2.27	1.28
	4	254	6	3	2	1.75	1.49	1.47
	8	422	16	4	1	2.06	0.92	2.18

The energy intensity and routine for cooking in Houses 8 and 19 are similar despite the households having two and four members respectively. However, there is a marked difference in their cooking patterns and demand profile. In the family of four with children (House 19) there is one clear peak for dinner in the evening, whereas the pensioner couple (House 8) spread out their cooking activity with multiple peaks throughout the day. The routine value for cooking indicates that both households are consistent and frequent in their respective cooking routines.

4.8   Synthesis

In this chapter, we developed and demonstrated a novel methodology for inferring the energy intensity and time use profile of domestic activities using smart meter data and qualitative interview data to build an ontology mapping appliance end-use to activities. We implemented the methodology to analyse the energy consequences of activities, and how they vary through time and between households. Our analysis showed that all energy intensive activities such as cooking and laundering can accurately be identified and that a significant portion of a household's electricity load can be attributed to a set of routine activities. From a total set of 10 activities, a subset of 4–6 activities can be inferred for any given household accounting for 13–40% of total monthly demand. The remainder is accounted for by other electricity consumption by cold appliances, base load, and the residual including lighting. By defining standardised metrics for both the energy intensity and routineness of activities, we could show how the time profile of activities varied considerably both within and between households.

The motivation for this work was the disconnect in our analytical framework (Table 2.1) between the instrumental view of SHTs for managing energy demand on the one hand, and the complexities of domestic life on the other. This disconnect is shown in Fig. 2.2 by the lack of cross-cutting linkages between vertical 'channels' of research. Activities such as cooking, watching TV or hobbies are ways in which householders spend their time at home. Using SHT data to make inferences about when and for how long activities are taking place sheds light on the variability, routineness and potential flexibility of domestic routines. Linking energy-intensive activities to their time profile may also help identify potential for load shifting and demand side management. For example, understanding which households have less routine in activities indicates 'opportunistic' activities which might be shifted off-peak to help alleviate supply constraints. These are important considerations for utilities and service providers to address in developing scalable products and services for the smart home market.

4.9   Suggested Further Reading

A longer version of this chapter was published as an open-access peer-reviewed article:

- Stankovic L, Stankovic V, Liao J, Wilson C (2016) Measuring the energy intensity of domestic activities from smart meter data. Applied Energy 183: 1565–1580. doi:10.1016/j.apenergy.2016.09.087

For other studies of domestic activities, their time profiles and energy intensities, we suggest:

- Jalas M, Juntunen JK (2015) Energy intensive lifestyles: Time use, the activity patterns of consumers, and related energy demands in Finland. Ecolog Econ 113 (0): 51–59. doi:10.1016/j.ecolecon.2015.02.016
- Torriti J (2017) Understanding the timing of energy demand through time use data: Time of the day dependence of social practices. Energy Research and Social Science 25: 37–47. doi:10.1016/j.erss.2016.12.004

References

Bertoldi P, Atanasiu B (2006) Residential lighting consumption and saving potential in the enlarged EU. In: Proceedings of 4th international conference on Energy Efficiency in Domestic Appliances and Lighting (EEDAL'06), 2006, pp 21–23

De Lauretis S, Ghersi F, Cayla J-M (2016) Time use, lifestyle and energy consumption: lessons from time use and budget data for French households. Paper presented at the energy: expectations and uncertainty, Bergen, Norway, 19–22 June 2016

DECC (2014) Smart metering implementation programme: smart metering equipment technical specifications version 1.58. Department of Energy and Climate Change (DECC), London, UK

Gram-Hanssen K (2014) New needs for better understanding of household's energy consumption—behaviour, lifestyle or practices? Architectural Eng Des Manage 10(1–2):91–107

Katzeff C, Wangel J (2015) Social practices, households, and design in the smart grid. In: ICT innovations for sustainability. Springer, pp 351–365

Liao J, Elafoudi G, Stankovic L, Stankovic V (2014a) Non-intrusive appliance load monitoring using low-resolution smart meter data. In: IEEE international conference on Smart grid communications (SmartGridComm), IEEE, 2014, pp 535–540

Liao J, Stankovic L, Stankovic V (2014b) Detecting household activity patterns from smart meter data. In: International conference on Intelligent Environments (IE), IEEE, 2014, pp 71–78

Murray D, Liao J, Stankovic L, Stankovic V, Hauxwell-Baldwin R, Wilson C, Coleman M, Kane T, Firth S (2015) A data management platform for personalised real-time energy feedback. Paper presented at the 8th international conference on Energy Efficiency in Domestic Appliances and Lighting (EEDAL'15), Luzern, Switzerland, 26–18 August 2015

ONS (2000a) National survey of time use. Office of National Statistics (ONS), London, UK

ONS (2000b) Survey on time use: activity coding list. Office of National Statistics (ONS) & Eurostat, London, UK

Schwartz T, Stevens G, Jakobi T, Denef S, Ramirez L, Wulf V, Randall D (2014) What people do with consumption feedback: a long-term living lab study of a home energy management system. Interact Comput 27(6):551–576

Stankovic L, Wilson C, Liao J, Stankovic V, Hauxwell-Baldwin R, Murray D, Coleman M (2015) Understanding domestic appliance use through their linkages to common activities. In: 8th international conference on energy efficiency in domestic appliances and lighting, 2015

Wilson C, Stankovic L, Stankovic V, Liao J, Coleman M, Hauxwell-Baldwin R, Kane T, Hassan T, Firth S (2015) Identifying the time profile of everyday activities in the home using smart meter data. Paper presented at the European Council for an Energy Efficient Economy (ECEEE) summer study, Hyeres, France, 1–6 June 2015

Zeifman M, Roth K (2011) Nonintrusive appliance load monitoring: review and outlook. IEEE Trans on Consum Electron 57(1)

Zoha A, Gluhak A, Imran MA, Rajasegarar S (2012) Non-intrusive load monitoring approaches for disaggregated energy sensing: a survey. Sensors 12(12):16838–16866