The electricity footprint of household activities - implications for demand models

Phil Grunewald*, Marina Diakonova

Environmental Change Institute, University of Oxford, South Parks Road, Oxford OX1 3QY, UK

**ABSTRACT**

It is an intuitive assumption that some activities require more energy than others. Bottom-up energy demand models therefore use time-use data to inform the timing of energy use. In this paper we present some empirical evidence to test the strength of this assumption.

Using data that simultaneously captures household activities and their coinciding electricity consumption, it is possible to relate one to the other. We validate the temporal accuracy of the approach with the example of reporting hot drinks and the distinct signature of kettle usage. Despite good data accuracy, the predictive power of reported activities for electricity use is modest. At time when activities that would subjectively be associated with high energy consumption are reported, electricity use is only about 7% higher than at times with activities of low energy association. For single occupant households the link is stronger with more than 30% difference between the two activity categories.

We conclude that demand models may need to take account of diversity and complexity in multi-occupant households and that more sophisticated regression techniques may be required to improve demand predictions based on time-use data.

© 2018 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license. (http://creativecommons.org/licenses/by/4.0/)

1. Introduction

The timing of energy demand could play a critical role for the extent to which variable renewables sources can be integrated into energy systems. Timing and flexibility of demand can dictate to a large extent the cost of integration and requirements for storage in low carbon energy systems [12]. This is especially the case for electricity, which is more costly to store than other energy vectors.

Time-use data has become widespread in attempts to better understand and model electricity use [18,10,19], the temporality of demand [1] and even intrinsic flexibility of demand [24]. Data is collected via paper diaries, which participants complete over one or two days, reporting for every 10 min period in plain text where they were, what they were doing as primary and secondary activity, as well as information about who they were with. The most recent UK survey also enquired about levels of enjoyment [4], Grunewald et al. [8] discusses limitations of the paper based approach introduces an interactive app as an alternative activity recording tool. The simultaneous collection of time use data with other sources of data has been developed by Gershuny et al. [5].

In the absence of data which simultaneously observes electrical load and activities, a plausible assumption had to be made by demand modellers to link the two sources of data: certain activities can be attributed to distinct load patterns or intensities. Household consumption and load profiles can thus be built 'bottom-up'. The wider assumptions underlying such models have been reviewed by McKenna et al. [11].

Alternative approaches have been proposed by Spataru and Gauthier [21], who use a variety of in-home sensors to establish electricity use related activities. Stankovic et al. [22] reverse the process and build up likely activity patterns based on appliance usage.

In this paper we test the validity and strength of the assumption that load can be directly attributed to activities reported in time-use surveys. With the first simultaneous collection of activities and household electricity profiles it is possible to compare and contrast activities against household electricity profiles.

In Section 2 we introduce and validate the data collection method, before analysing relationships between activities and electrical load in Section 3. The results and their implications are discussed in Section 4. We close with conclusions for future energy modelling and time-use data collection.

* Corresponding author.

E-mail address: philipp.grunewald@ouce.ox.ac.uk (P. Grunewald).

https://doi.org/10.1016/j.enbuild.2018.06.034

© 2018 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license. (http://creativecommons.org/licenses/by/4.0/)
2. Method

We seek to test the following hypothesis: The electricity use of a household can be predicted as high or low depending on the type of activity reported during a given hour.

Data used for this analysis have been collected as part of the Meter Study [7]. These data are the first of their kind and we therefore explain their collection method in some detail here.

2.1. The sample

Electricity readings and activity records are collected from UK households as part of an ongoing study [6]. Participation in the study is voluntary and the sample is therefore not representative of the general UK population. The study is promoted online, via radio, and through campaigns at selected community events. To motivate participation a chance to win the cash equivalent of a year’s worth of electricity is offered. Some selection biases therefore apply. In particular high income groups are over-represented, as well as adopters of solar PV and electric vehicles (see Table 1). While these biases affect overall consumption and to some extent the timing of demand, for the purposes of this analysis we believe that these biases are unlikely to affect our findings for the fundamental relationship between activities and electrical load.

Detailed socio-demographic information about the sample is collected as part of the registration process, such that self-selection biases can be identified and balanced over time. This study encourages all household members above the age of eight to participate. This makes the data distinct from most conventional time-use surveys, where individuals, rather than whole households participate. In the context of electricity, which is recorded at household level, it is therefore now possible to explore collective activities. We will differentiate in the analysis between single and multi occupant households to highlight the importance of this distinction. The analysis is limited to activities that were reported to be performed while at home. The resulting sample sizes are shown in Table 2.

Each participating household is given a choice of 3 randomly assigned dates. Activity and electricity recordings are taken over a 28 h period starting at 5pm, thus capturing two of the typically most energy intensive periods between 5pm and 7pm.

| Feature          | Group | Sample [%] | National [%] |
|------------------|-------|------------|--------------|
| Home ownership   |       | 85         | 64           |
| Income           | <15,000 | 6       | 19           |
|                 | <25,000 | 13      | 22           |
|                 | <35,000 | 9       | 16           |
|                 | <50,000 | 21      | 17           |
|                 | ≥50,000 | 51      | 27           |
| Occupants       | 1–2   | 57        | 64           |
|                 | 3–4   | 37        | 30           |
|                 | > 4   | 2         | 7            |
| Age             | Under 18s | 26       | 23           |
|                 | 19–50 | 47       | 44           |
|                 | Over 50 | 24      | 35           |
| Pets            | Dogs  | 10        | 24           |
|                 | Cats  | 24        | 17           |
|                 | Fish  | 6         | 8            |
| Appliances      | PV    | 14        | 4            |
|                 | Electric Vehicle | 4       | 0.4          |
|                 | Washing machine/dryer | 99     | 97           |
|                 | Dishwasher | 51       | 45           |

Table 2 Sample sizes. Activities refer to total number of reporting instances.

| Property                  | All | Single occupants |
|---------------------------|-----|------------------|
| Households                | 140 | 20               |
| Activities                | 7628| 586              |
| Home activities           | 5145| 458              |

2.2. Data collection

Participating households are sent a parcel prior to their assigned date. This parcel contains the electricity recorder, activity recorder(s) and an instruction booklet.

Electricity recordings are taken every second with a current clamp attached below the household’s electricity meter. Participants attach and remove this device themselves, thereby avoiding the need for costly and intrusive visits by engineers. Consumption of gas, coal, wood and other fuels are not recorded. Instead, the fuel type of different heating and cooking appliances are captured as part of the household survey.

Activities are recorded using a dedicated app, pre-installed on purpose built devices. The app guides users through a series of six options per screen (see Fig. 1), always starting with location, followed by series of activities and concluding with the number of other people part-taking in the activity and one’s enjoyment of it. The decision tree with six branches per screen quickly leads to a detailed description of activities. Unlike paper diaries conventionally used for time-use data collection [3], the app encourages the provision of energy relevant details, such as the particular nature of an activity (hot or cold meal) and a prompt for appliances that may have been in use, if relevant.

Users are encouraged to report activities at the time, but entries can be made retrospectively and also into the future. Each user selection is recorded with one of 144 time-use codes, the time of reporting and the time of the activity itself. In addition the location, number of other people and perceived enjoyment are also recorded. More detail about the functionality of this app is discussed in Grunewald et al. [8].

2.3. Validation

Verifying the accuracy of self reported activities is inherently difficult. Gershuny et al. [5] claim that their validity is not in doubt and use objective instruments, including video footage, to support this assertion by comparing the total duration of activities reported and observed. For their sample of 131 people, only TV, eating and reading diverge between the video footage and the diaries. Surprisingly, the amount of time watching TV is over-reported and reading is under-reported, each by nearly 10%. This is contrary to the expectation that non-desirable activities get under-reported and more desirable ones over-reported.

Reporting of ‘hot drink’ related activities, when carried out at home, lend themselves to testing the accuracy of the activity records used here. Such activities are reported frequently and the performance of the activity is broadly neutral in terms of social desirability. 53% of individuals and 73% of households report making a hot drink or use of a kettle during their day at least once.

The electricity signature of a kettle is very distinct and usually short lived, such that it provides a helpful marker for temporal accuracy, as shown in the illustrative examples in Fig. 2. It is less suitable as a test for false negatives. If a hot drink has been reported and no kettle signature can be detected it could either be that the activity was reported wrongly or too inaccurately time-wise, or that the hot drink did not involve an electric kettle, but
Fig. 1. Activity entry sequence with optional follow up entries.

Fig. 2. Coincidence of electrical load signature of a kettle with the reporting of a ‘hot drink’ like activity. Illustrative selection of cases.

for instance a gas fired kettle. 26% of events fall into any of these categories.

For all other cases the time difference $d_t$ of the reported activity and the corresponding kettle signature can be compared. A histogram of the error between the two events is shown in Fig. 3.

In over 67% of cases the reporting accuracy is within 10 min of the observed electricity signature. Narrowing the scope to explicit reporting of the appliance ‘kettle’ itself improves this figure to 80%.

The high quality of temporal alignment between activities and their associated appliances arising from this collection method allows us to broaden the analysis to activities that are less directly associated with an easy to identify appliance. Kettles have a very prominent signature due to their high power and short use periods. In energy terms they are rather less significant and we therefore consider more energy intensive activities and appliances in the following section.

2.4. Analysis

The activity and electricity records undergo several steps of quality assurance before use. Activity records with fewer than 7 entries are disregarded as insufficiently completed, consistent with quality standards in time-use research. Continuous periods of electricity readings with less than 20 Watt are also excluded. In some cases this is the result of failure to attach the electricity recorder correctly or at the right time. Activities that were recorded before or after the device is attached are thus not considered.

For this analysis, only activities performed inside the home are included, since only these can be reasonably expected to have a direct bearing on household electricity use. This leaves 5145 activities for use in this analysis including 458 for single occupants (see Table 2).

To analyse time-use data a taxonomy of seven categories has become established in time-use research [9,22,2]. These are: care
for self, care for others, care for household, food, recreation, travel and work. However, for energy research this categorisation does not distinguish well between low and high uses of energy.

Subsets of activities have therefore been created, which could be specifically related to energy use. We use an activity framing and an appliance framing. Energy intensive activities include particular types of housework, preparation of hot meals, screen time, etc. The appliance framing only considers events that explicitly name appliances with high energy consumption (use dishwasher, vacuum cleaning, oven, etc.).

### 2.4.1. Energy related activities

The assumption that reported activities can be used to infer higher electricity use at the time they are performed is based on the intuitive notion that some activities are inherently more energy intensive than others. Table 3 shows a subjective list of activities that fall into such perceived high and low use classes. This is a subjective subset of activities, since not all activities lend themselves to this categorical differentiation. Some activities have no apparent bearing on electricity use, and others, such as ‘food preparation’ are ambiguous and could be performed with high or low use of energy.

This subjective list shown in Table 3 is informed by similar attributions made by Richardson and Thomson [17], Lauretis et al. [10], Torriti [23] and others. The labels in this table can represent more than one activity code, i.e. ‘dishwasher’ includes activities like ‘loading the dishwasher’.

It is important to note that these attributions were constructed a-priori and not optimised for electricity correlation. An alternative approach could be to use clustering methods to define categories. Given the vast number of activity variables, this approach is likely to lead to false sense of causality and is avoided here. Furthermore, the hypothesis set out above is about the predictive power of pre-selected activities for electrical loads. A card sorting exercise with experts may also help to define similar categorisations. For this paper activities are manually categorised.

Each activity or its category is linked with the electricity use of the associated household over four time periods. The average load (in Watt) is calculated for 10 and 60 min periods preceding the event and also for 10 and 60 min following it.

#### 2.4.2. Appliance use

The app based activity collection approach allows participants to be specific about appliance use. Appliances can be entered directly, or in response to follow-up questions, after reporting activities which are likely to involve appliances, such as hot meal preparation in the example in Fig. 1. Energy intensive appliances shown in Table 4 make up a set for separate analysis. Kettles, which have already demonstrated good alignment with activity reporting are not included in this set. While they have a clear power signature, their use tends to be significantly shorter than the 10 and 60 min periods considered in the following Section.

### 3. Results

Households report on average 35 activities over the 28 h reporting period. The number of reported activities in a given hour is positively correlated with electricity use (Fig. 2). In general electricity consumption tends to be below average during periods of no reporting, such as sleep (some participants with night storage heaters and electric vehicles are notable exceptions). This explains the step change between ‘0’ and ‘1’ activity reported. While no reported activities could just be the result of participants not reporting their activities, any value greater than ‘0’ implies active occupancy, meaning at least one person in the household is awake and active. [8]

The relationship in Fig. 2 suggests that the activity intensity itself may provide a proxy for consumption, regardless of the type of activities being performed. What Southerton [20] refers to as ‘hot spots’ in peoples lives, may therefore translate directly into hot spots of electricity consumption. The trend is approximately 50 Watt per activity.

For a more detailed understanding of demand it is possible with these data to explore the electricity footprint of activities themselves.

Fig. 5 shows activities ranked in order of the median electricity use of the household in the hour of reporting. Boxes span the surrounding 25th percentiles of average electricity readings during that hour. Where such boxes are not shown, an insufficient number of instances of an activity was reported (Fig. 5).
Table 5  
Multi occupant activities.

| Period          | Difference [%] | t    | p     |
|-----------------|----------------|------|-------|
| Previous 60 min | 11             | 3.96 | 0.00008 |
| Previous 10 min | 14             | 4.20 | 0.00003 |
| Subsequent 10 min | 7             | 1.93 | 0.05339 |
| Subsequent 60 min | 7             | 2.59 | 0.00962 |

Table 6  
Single Occupant Activities.

| Period          | Difference [%] | t    | p     |
|-----------------|----------------|------|-------|
| Previous 60 min | 20             | 2.62 | 0.00915 |
| Previous 10 min | 44             | 3.61 | 0.00035 |
| Subsequent 10 min | 35           | 2.86 | 0.00447 |
| Subsequent 60 min | 34           | 3.06 | 0.00237 |

Table 7  
Multi occupant appliances.

| Period          | Difference [%] | t    | p     |
|-----------------|----------------|------|-------|
| Previous 60 min | 19             | 4.75 | -0.0001 |
| Previous 10 min | 29             | 6.61 | -0.0001 |
| Subsequent 10 min | 33           | 8.02 | -0.0001 |
| Subsequent 60 min | 25           | 6.86 | -0.0001 |

Table 8  
Single occupant appliances.

| Period          | Difference [%] | t    | p     |
|-----------------|----------------|------|-------|
| Previous 60 min | 18             | 1.53 | 0.12748 |
| Previous 10 min | 54             | 4.48 | 0.00001 |
| Subsequent 10 min | 42           | 2.84 | 0.00474 |
| Subsequent 60 min | 34           | 2.29 | 0.02268 |

The diversity of median readings in Fig. 5 invites the conclusion that activity codes on the left of the graph could be used to predict high electricity use and those on the right low use. However, closer inspection does not support this approach. Very similar activities can be found on both ends of this distribution. Laundry, for instance, appears as a high energy intensive activity, as well as a low energy activity, since this activity can be performed in an automated form (using a washing machine) or a very manual form (folding and sorting clothes). Depending on whether the participant entered the activity via ‘Home > Appliances’ or ‘Home > House work > Sorting things’ the label Laundry can be one or the other.

Fig. 6 compares the electricity use for activities that have been subjectively classified as high or low energy intensity in Table 3. Four time zones are shown: the average use over the 60 min and 10 min period preceding and following an activity being reported.

The ‘high energy’ activities (dark bars) show higher energy consumption than the reference case (all in home activities - blue line) across all four time periods considered. Conversely, ‘low energy’ activities show consistently lower electricity use. While most of these data points show statistically significant differences between ‘low’ and ‘high’ use activities (Tables 5–8), the differences are very modest indeed. For multi-occupant households (Fig. 6(a)), the differences range between 7% and 14%. It is noteworthy that despite the differences being small, they are statistically significant with $P \leq 95\%$ in all but the 10 min following the reported activity.

The comparison with single occupant households (Fig. 6(b)) helps to explain some of the weak differentiation. Here the differences are well above 30%. Much of this difference is therefore likely to be blurred in multi occupant households by low energy activities being reported by some household members while others engage in high energy activities - all of which get attributed to the same load.

Using the reporting of high energy use appliances alone, the signal is predictably stronger. During the 10 min surrounding the appliance use being reported, electricity use is around 30% higher in multi-occupant households and over 40% higher in single occupant households.

4. Discussion

The modest coincidence between reported activities and electricity consumption can have several reasons.

4.1. Activities have varying energy intensities

The same activities can be performed in high and low energy forms. The time-use app used for the data collection constitutes an advance over conventional paper diaries, in that it is able to follow up on the context of an activity, such as whether washing dishes is performed by hand (low energy) or a machine (high energy). The differentiation in Table 3 is taking advantage of these details. However, diversity remains on both sides of the arbitrary ‘high’ and ‘low’ energy use divide as shown by the wide 50th percentile bands in Fig. 3.

4.2. Activities overlap

Activities can, and often are, reported in clusters. The notion of ‘hot spots’ by Southerton [20] results in busy periods when people report multiple high and low energy activities at similar times, resulting in both being attributed to the same load. Activities with little intrinsic energy use appear to have a higher energy footprint as a result of this conflation. Activities therefore generally coincide with above average consumption (see Fig. 4).

With sufficient quantities of data more refined regression approaches may allow to disassociate these activity combinations.

4.3. Household consumption often is the result of collective, rather than one individual’s actions

In multi occupant households activities not only overlap per person, as in 4.2, but different people can perform very different activities at the same time, all of which are attributed to the same collective load profile. The comparison with a small number of single occupant households suggests that this effect is significant.
More sophisticated analysis on larger samples may be able to quantify the effects of diversified versus highly synchronised household activities and their role in shaping load profiles. As with 4.2 it may also be possible to use regression techniques to improve on the attribution of load to individual activity patterns.

4.4. Energy uses and activities can be decoupled in time

One of the recent priorities in energy demand research is the identification of opportunities for flexibility. Decoupling the timing of energy service provision from the timing of energy consumption could offer valuable opportunities in this area. Where this decoupling is already taking place, the association of the timing of activities and electricity consumption is weakened. For instance, whereas a decade ago ‘Watching TV’ would have seen a directly associated electrical load from a TV set, it is now increasingly likely that mobile devices are in use, which can be charged at times other than their use.

Understanding the trends in this decoupling over time could provide helpful insights into the scope for load shifting and flexibility.

4.5. Many energy uses are activity independent

Baseline consumption is an obvious example that much electricity consumption is independent of household activities. It may therefore be appropriate to remove this ‘offset’ from the data, which would result in a stronger differentiation between high and low use activities in relative terms.

The comparatively stronger association between high use appliances and electricity consumption is of course a trivial result, in that it merely confirms that these appliances do indeed use significant amounts of electricity. It does however validate the method to some extent and allows for some interesting follow up analysis on the timing of their use and how these time signatures relate to other activities.

For this type of analysis it is no longer the temporal coincidence of an activity with an electrical load, but the rather more complex patterns of activity sequences and how they shape the times of high and low electricity consumption. Activities that do not necessarily have a strong bearing on load at the time may nevertheless be significant in shaping load at other times. Examples of such activities could be ‘arriving home’ or ‘collecting children’.
5. Conclusions

This paper set out to test the hypothesis that household electricity consumption can be predicted for a given hour based on whether energy intensive and non-intensive activities were reported in that hour.

Using new data, which collected activities and electricity consumption profiles in parallel, we tested this hypothesis by comparing the electricity use before and after reporting of activities subjectively classified as high or low in energy intensity.

While statistically significant differences are observed, the scale of the differences is modest and can be less than 10% for multi-occupant households. Five reasons have been presented that could explain these relatively small differences. 1) The same activities can be performed with varying energy intensities, 2) high and low energy intensive activities are often reported at similar times leading to averaging, 3) multi-occupancy blurs attributions, 4) energy services can be decoupled from energy use in time and 5) some energy uses, such as baseline, are activity independent.

The hypothesis must therefore be rejected and caution should be taken when attempting to construct detailed demand models from time-use data alone, especially when attempting to replicate multi-occupant household profiles from time-use records of individuals.

Time-use data, especially when collected in conjunction with electricity consumption data, does however yield valuable insights into the patterns and temporality of demand. The collection methods have been validated for their temporal accuracy of reporting and the ability to attribute load patterns to activities and appliances. Larger samples and more refined regression techniques are likely to reveal valuable relationships that can inform our understanding of the timing of demand, its diversity across society, trends over time and ultimately changes in its flexibility.

Acknowledgement

This work is supported by the Engineering and Physical Sciences Research Council (EPSRC) under grant EP/M024652/1.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.enbuild.2018.06.034.

References

[1] B. Anderson, Laundry, energy and time: insights from 20 years of time-use diary data in the United Kingdom, Energy Res. Social Sci. 22 (Supplement C) (2016) 125–136. https://doi.org/10.1016/j.erris.2016.09.004

[2] K. Ellegård, K. Vrotsou, J. Widén, VISUAL-timeimps/energy use: a soft ware application for visualizing energy use from activities performed, in: Conference Proceedings 3rd International Scientific Conference on “Energy Systems with It, 2010. pp. 1–16.

[3] Eurostat, Harmonised European Time Use Surveys, Office for Official Publications of the European Communities, 2014 2008 guidelines.

[4] J.L. Gershuny, O. Sullivan, United Kingdom Time Use Survey, 2014-2015, 2017. SN: 8128 UK Data Service http://doi.org/10.5255/UKDA-SN-8128-1.

[5] J. Gershuny, T. Harris, A. Doherty, E. Thomas, K. Milton, P. Kelly, C. Foster, CAPTURE24: Testing Self-Report Time-Use Diaries Against Objective Instruments in Real Time, Centre for Time Use Research, University of Oxford, 2017 Working paper.

[6] P. Grünwald, R. Layberry, Measuring the relationship between time-use and electricity consumption, in: Ecree 2015 Summer Study Proceedings, 2015, pp. 2087–2096.

[7] P. Grünwald, Measuring and Evaluating Time-Use and Electricity-Use Relationships (Meter), Engineering: Physical Sciences Research Council (EPSRC), 2015 Early Career Fellowship Ref. EP/M024652/1.

[8] P. Grünwald, M. Diakonova, D. Zilli, J. Bernard, A. Matousek, What we do matters – a time-use app to capture energy relevant activities, in: Ecree 2017 Summer Study Proceedings, 2017, pp. 2085–2093.

[9] D. Lader, S. Shott, J. Gershuny, The Time Use Survey, Office for National Statistics (ONS), 2006.

[10] S.D. Lauritis, F. Gherzi, J.-M. Cayla, Energy consumption and activity patterns: an analysis extended to total time and energy use for French households, Appl. Energy 206 (2017) 634–648. https://doi.org/10.1016/j.apenergy.2017.08.180.

[11] E. McKenna, S. Higginson, P. Grunewald, S.J. Darby, Simulating residential demand response: improving socio-technical assumptions in activity-based models of energy demand, Energy Eff. (2017) 1–15 Springer, doi:10.1007/s12053-017-9525-4.

[12] National Infrastructure Commission, “Smart Power.” National Infrastructure Commission report, National Infrastructure Commission, 2016.

[13] ONS, Population Estimates for UK, England and Wales, Scotland and Northern Ireland: Mid-2015, Office for National Statistics, 2015 Online https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/bulletins/annualmidyearpopulationestimates/md2015.

[14] ONS, Families and Households in the UK: 2016, Office for National Statistics, 2017 Online https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/families/bulletins/familiesandhouseholds/2016.

[15] ONS, Percentage of Households with Durable Goods, UK, Office for National Statistics, 2017 Table A45 https://www.ons.gov.uk/peoplepopulationandcommunity/personalhouseholdfinances/expenditure/datasets/percentageofhouseholds withdurablegoods3tablea45.

[16] ONS, Family Resources Survey, 2015/16, Office for National Statistics, 2018 Online https://www.gov.uk/government/statistics/family-resources-survey-financial-year-201516.

[17] J. Richardson, M. Thomson, CREST Domestic Electricity Demand Model, CREST (Centre for Renewable Energy Systems Technology), Loughborough University, 2007 https://dispace.liboro.ac.uk/dispace-jspu/handle/2134/5786.

[18] J. Richardson, M. Thomson, D. Infield, C. Clifford, Domestic electricity use: a high-resolution energy demand model, Energy Build. 42 (10) (2010) 1878–1887. http://www.sciencedirect.com/science/article/pii/S0378778810001854.

[19] A. Sekar, E. Williams, R. Chen, Changes in time use and their effect on energy consumption in the United States, Joulle (2018) 2542–4785, doi:10.1016/j.joule.2018.01.003.

[20] D. Southerton, Squeezing time: allocating practices, coordinating networks and scheduling society, Time Soc. 12 (1) (2013) 5–25 Sage Publications.

[21] C. Spathar, S. Gauthier, How to monitor people ‘smartly’ to help reducing energy consumption in buildings? Archit. Eng. Des. Manage. 10 (1-2) (2014) 60–78, doi:10.1080/17452007.2013.837248.

[22] L. Stankovik, V. Stankovik, J. Liao, C. Wilson, Measuring the energy intensity of domestic activities from smart meter data, Appl. Energy 183 (2016) 1565–1580 Elsevier.

[23] J. Torriti, Understanding the timing of energy demand through time use: data: the day of dependence of social practices, Energy Res. Soc. Sci. 25 (2017) 37–47 Elsevier.

[24] J. Torriti, R. Hanna, B. Anderson, G. Yehoah, A. Druckman, Peak residential electricity demand and social practices: deriving flexibility and Greenhouse gas intensities from time use and locational data, Indoor Built Environ. (2015) SAGE Publications, 1420326 × 15600776.

[25] UKERC-EDC, Domestic washing machine – appliance ownership levels, Data Repository, Energy Research Centre Energy Data Centre (UKERC-EDC), UK, 2017 http://data.ukerc.rl.ac.uk/simplebrowse/edc/efficiency/residential/Appliances/Domestic_Washing_Machines.