What we do matters – a time-use app to capture energy relevant activities

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Keywords

demand patterns, demand analysis, social practices, activity patterns, electricity use

Abstract

High expectations rest on demand side response to aid the reliability of future electricity systems and to reduce costs. The extent of the potential contribution depends among other things on what that demand is used for. Some uses could be more flexible than others. Some may respond to price signals, others may require different forms of incentive or changes to material or social contexts. Our understanding of the temporal relationship between the activities and the resulting electricity patterns is still in its infancy.

This paper presents a novel research tool to combine electricity data collection with activity information at the household level. We critically review established methods to time-use collection and propose a range of innovations to improve their suitability for energy related research with the aim to establish 'what people use electricity for'. Innovations include: 1) A six-way decision tree allows to discriminate 714 in-home activities with fewer than five screen interaction. 2) The recording of instances in time ('constructive time perspective') greatly reduces the user-interface complexity. 3) Virtual rewards have been shown to improve participation and even introduce a degree of recording competitiveness within households.

The functionality of this open source mobile app is presented alongside feedback and data from its deployments in UK households. We discuss advantages and drawbacks of this approach in relation to conventional paper-based methods and point towards future research opportunities this approach could enable.

Introduction

Through a combination of supply networks and supply side storage, modern society has achieved a near complete decoupling in the temporality of consumption from locally available resources. This applies to food, water, energy and information alike. In these societies food can be consumed at any time of year, regardless of seasonality or origin; water is available irrespective of recent local rainfall; and information is reaching similar levels of ubiquitous availability via the internet. Energy, too, has become available as and when needed. The expectation level of this provision has become such that even brief supply disruptions can be perceived as crisis-like events.

Consumption patterns in all these domains are presently predominantly demand driven. Infrastructures are specified and sized to meet whatever the demand side 'demands'. The relative ease with which fossil fuels can be extracted, transported and stored has allowed for these structures to develop at acceptable (economic) costs. Lower carbon sources, which are more dependent on temporally changing resources, would be costlier to integrate at scale under this paradigm. A return to more sustainable societies may therefore necessitate among other things a re-appreciation of the rhythms, seasonality and availability of local resources.

It has been shown that the overall societal cost is highly sensitive to the ability of demand to respond to the availability of low cost/low carbon sources. By 2030, the UK's National Infrastructure Commission estimates that up to £8,1 bn could be saved annually if 'smart solutions' are taken full advantage of (National Infrastructure Commission (2016)). To what extend flexible demand can contribute towards this effort remains subject of conjecture. Several studies have attempted to test demand side responsiveness through price signals. Results consistently show peak demand reductions in the region of 2–8 % (Schofield (2015), CER (2011), Sidebotham (2015)). Because these studies only monitor total household load, it is difficult to discern how the load reduction was achieved in practice. The data is inconclusive about the extent to which service expectations were left unmet or merely rearranged. A deeper understanding of the activities and dynamics that make up load patters may yield new insights into more effective ways to deliver sustained changes to load profiles. Walker (2014) and Huebner et al. (2015) point out that social factors play an important role in shaping load profiles. Price signals may therefore not necessarily unlock the broad range of possible responses effectively. Grünewald (2016) theorises that there could be as many as eight different forms of demand side flexibility, many of which depend on the sequence and arrangement of activities.

A first step towards an understanding of 'what electricity is used for' is the detailed collection of time resolved appliance level data, such as Zimmermann et al. (2012). Stankovic et al. (2016) build on such approaches to infer the activities being performed in the household. For instance, a TV that is running could suggest 'recreational activities'. However, it is also possible for this TV to be running in the background - a difference that could have a bearing on the degree of flexibility for this load.

Grünewald and Layberry (2015) propose to go further and directly interrogate household activities while recording high resolution load profiles. The parallel collection of time-use and electricity consumption offers deeper insights into the relationship between activities and load profiles, and ultimately the dynamics that could deliver greater flexibility. The Meter study undertakes this research. Between 2015 and 2020 hundreds of UK households participate in the study with two overarching aims: 1) To better understand the temporalities of household activities and their relationship with electricity use; and 2) building on this understanding to evaluate the effectiveness of different incentives to support demand side flexibility. Self administered electricity recorders and diary devices will be used by UK households to gather the relevant information (Grünewald (2015)). Electricity recordings are taken with 1 second resolution from 5 pm to 9 pm the following day, thus covering two high demand periods (5 pm–7 pm) (see Grünewald (2017b)). At a later stage controlled interventions will be introduced to observe changes in load profiles and the underlying shifts and alterations in activity patterns that delivered these.

This paper will discuss ways to collect the accompanying activities and the importance of their contexts. First we review existing tools, both paper and app-based, before outlining a new approach, which allows to specifically interrogate energy relevant activities, while keeping participant burden to a minimum. We present results obtained using app-based activity and electricity consumption data and discuss limitations and opportunities for development.

Collection of time-use resources

Time use research has developed and refined instruments to collect and code activity information for several decades. Multinational records extend back to the 1960s (Gershuny and Sullivan (2003)). In this section we present the principal collection methodology and recent attempts to translate these into apps.

DIARY COLLECTION

Hand written personal diaries have become an established tool in time-use research. The general format has changed little over the years, and some fields have been added or modified over time. A recent sample is shown in Figure 1.

These diaries have 13 columns of information for each entry. They cover time, activities (primary and secondary), location and categories of people (not the number) one was with. Two columns were added in the 2015 UK survey: "Did you use a smartphone, tablet or computer" and "How much did you enjoy this time?".

These diaries are issued to participants as A5 booklets with 48 pages, including instructions, two days worth of diary forms (16 pages each), a working-hours diary for 7 days and a checklist. It does not include any questionnaires or the consent form.

Paper diaries have proved effective and convenient for participants to carry with them and complete throughout the days. It is, however, not possible to tell if entries were made near the time or belatedly. The checklist therefore asks when the diary as a whole was completed.

The duration of an ongoing entry can conveniently be marked with a line (see Figure 1). The free text format allows the participant to formulate their entries as brief or elaborate

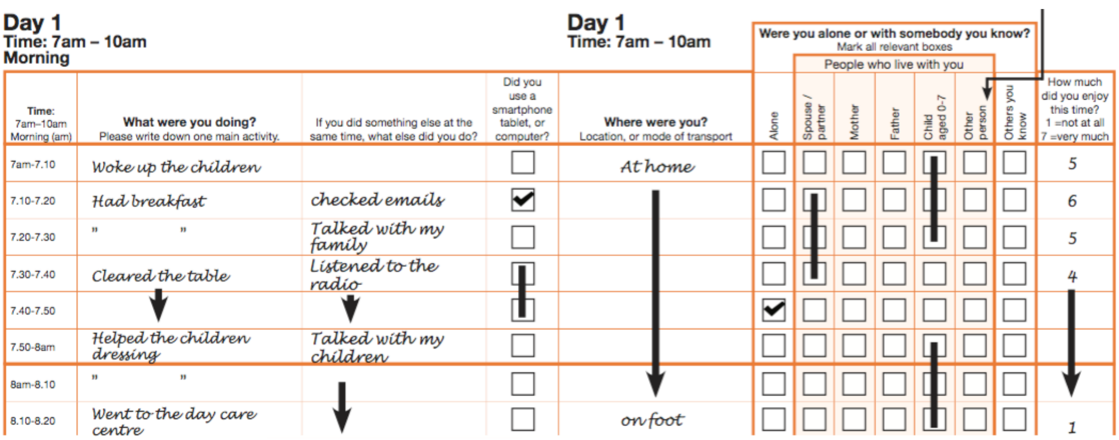

Figure 1. Illustrative example from the 2015 UK Time Use Survey.

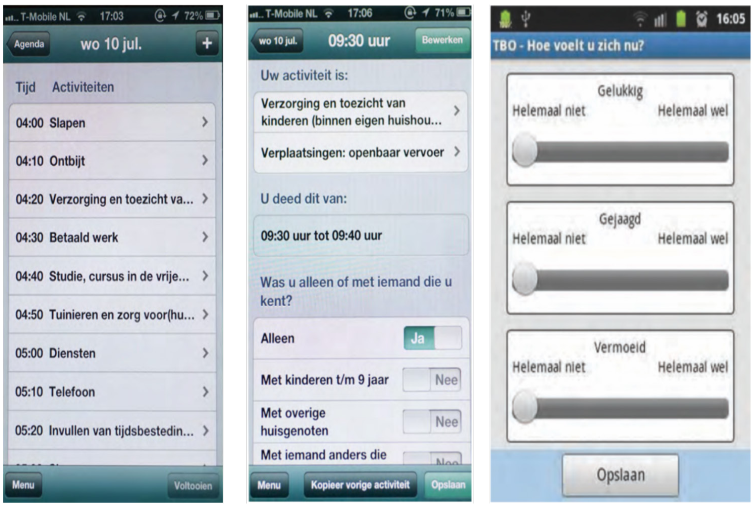

Figure 2. Multi input interface for time-use entries (Sonck and Fernee (2013).

as they choose. It falls to the researcher or analyst to decipher, interpret and map the entries onto the time-use code classifications and break them down into so-called 'episodes' (and episode is an activity that spans rows with no alteration in any column). This can be a time and labour intensive process.

TIME USE CODING

The Harmonised European Time Use Survey (HETUS) attempts to create a consistent methodology to allow comparisons between different studies by region or longitudinally. Around 280 activity codes are currently in use (eurostat (2014)).

Consistency is desirable and necessary for such comparisons. Anderson (2016) argues that subtle changes in the methodology and terminology can pose challenges for comparative analyses. Such changes include the definition of the time periods themselves. In 1974 the time intervals participants were asked to report on was 30 minutes, in 1983 15 minutes, and more recently 10 minutes have become the dominant unit. The difference not only affects the data format. Activities can be reported systematically differently. Short activities may not get reported at all when the time window in question is longer and thus the activity distribution can be skewed.

The coding of activities into numerical categories has also changed over time, either because the research questions evolve or due to societal and technological changes. Food preparation was initially a single category and became more refined in later studies to distinguish baking from making a cup of tea. Curiously, 'making a hot drink' is not part of the current HETUS codes.

Furthermore, the meaning of categories can differ between cultures and over time. "Watching TV" has changed in response to on-demand mobile video content and may not longer be reported as such. New categories are therefore needed to reflect these changes, such as 'watching videos online'.

APP-BASED DIARIES

The rapid emergence of smartphones over the past decade have led to suggestions that these could be used as diary instruments. Smartphones have some specific advantages over paper-based instruments, as well as drawbacks, which we will explore here.

Their interactivity allows to create a more responsive and tailored engagement, for instance by raising or suppressing questions or response options depending on context. Furthermore, they offer a rich system of sensors and recording options than can enable innovative approaches for time-use research.

Commercial apps are available to record activities, based on directly provided information by the user, as well as through inferences, such as location or activities performed on the phone itself (e.g. reading emails, social media, watching videos…). Applications range from time sheet completion to productivity tools promising to assist in better time management. The role of the user can range from passive to highly engaged. Commercially such apps can be attractive because of the insights they give into their user, and the direct marketing opportunities this offers. For academic research we have to be mindful of the ethical implications of this type of data mining, especially when the degree of data collection and the resulting insights are not fully comprehensible to users.

In research the time-use diary methodology has also been translated into mobile apps. Examples include Giraldo Ocampo (2015) and Fernee and Sonck (2014). Their approach remains broadly true to the HETUS methodology and captures all the main fields shown in Figure 1.

As in the hand-written diary, activities are recorded for each of the 144 ten minute periods that make up a day. Sonck and Fernee (2013) reduced the number of activity codes from 280 down to 35 activities grouped into 11 categories (Personal care, Domestic work …) to make the selection process more manageable.

The app has been field tested with more and less experienced smartphone users (people who had to be issued a phone). Sonck and Fernee (2013) found that inexperienced users were less likely to engage with the app effectively. Only 55 % complete their first diary day compared to 80 % of experienced users (N = 100). While smartphones become ubiquitous it is still worth noting that interface complexity could inhibit certain users and bias results. Users have to operate a range of sliders, toggle buttons, scroll windows, menus and pop-up screens (see Figure 2).

Aside from the interface complexity, the format is not well suited for the interrogation of activities related to electricity consumption patters. Firstly, the focus on 144 ten minute periods prioritises time at the expense of activities with only 35 codes for activities. For a better understanding of energy use, more rather than fewer activities need to be differentiated. Often subtlety of context is required (does 'meal preparation' involve a cooker or does 'doing laundry' use a washing machine?). The conventional format, even with provision for 'secondary activity', fails to pick up such details.

The next section will suggest some deviations from the standard methodology with the aim to enhance usability and suitability for energy related research questions.

A new approach to app-based activity collection

The app proposed here was developed for use alongside an electricity recorder (see Grünewald and Layberry (2015)), yet a wide range of other applications could be envisaged. Further detail about the app is available from the open source repository and documentation (Grünewald (2017a)).

The app was developed with the following guiding design principles:

- **Ease of use:** the interface should be accessible to any moderately literate person above the age of eight, without a manual. The number of interactions needed should be kept to a minimum.
- **Focus on activities:** A rich level of detail on activities and contextual information should be made easily accessible.
- **Rewarding experience:** users should perceive the process as pleasant, rather than a challenge or a burden.

The implementation of these design principles has resulted in some methodological changes. An iterative process of wireframing, prototyping and field testing led to a new approach to activity collection.

This development process continuously refined the app-based on user feedback. A feedback feature was built directly into beta version of the app, such that each entry could be rated in real time on a five-point scale depending on how well the selection described what people attempted to enter. Very detailed or broad descriptions have left some trial participants confused or unsatisfied with their own entries. Furthermore, the option to manually overwrite entries with free text gives valuable feedback, where additional options were seen to be desirable. Finally, the app is used to code up hand written diaries, thereby testing that all freehand entries are translatable with sufficient fidelity. Some of the resulting changes and their implications are explained in the following sections.

CONSTRUCTIVE TIME PERSPECTIVE

People do not experience, nor do they tend to think about time, as a sequence of 10 minute blocks. The framing in this 'analytical time perspective' gives precedence to time over activities (Ellegård (1999)). Activities that take longer tend to dominate the reporting, in favour of shorter, but potentially more important activities. Allowing participants to choose what and when to report, affords them a 'constructive time perspective' and brings the activities themselves to the fore. This approach also significantly simplifies the interface. We will discuss the implications for entering and analysing data.

Paper diaries make the division of a day into 144 slices relatively easy to handle over 8 double spreads in the booklet. A small mobile screen is more difficult to navigate, especially if all 13 columns of information are to be displayed without a deep nesting of menus (note that the entry screen extends beyond the visible space in Figure 2, thereby hiding some fields unless scrolled). One could ask for each activity when it started and when it ended. If the end is in the future a recursive repetition of requests may result to 'close off' any ongoing activities. Early prototypes suggest that this process could become confusing for users.

Since mobile devices already 'know' the current time, it is possible instead to take snapshots of the present moment without the need to even ask about the time. This is conceptually different and can be cognitively easier for participants. "What are you doing now" is less ambiguous than "What did you do during this 10-minute period". Past activities can be reported with a single 'time setting', or a given time in the past can be prompted by the app.

The focus on 'points in time' omits durations. Some participants expressed a need to be able to report when an activity ended. Such a feature has been introduced (see 'Edit' screen Figure 3f), recording the 'end' also as a point in time.

Not collecting the duration of each activity explicitly comes at a price. The sum of activities does not add up to a 'time budget' of 24 hours per day. Whether this is acceptable depends on the research aims. An analysis of 'time spent' on particular activities is not possible without asking about start and end times. However, if the analysis focuses on context, sequences and relationships, then 'what people do at a given time' may yield more relevant data.

NAVIGATING ACTIVITIES

Finding the right activity within a list of tens or even hundreds of possible activities is not a feasible option. A decision tree, guiding users through the options with a limited number of choices at each node, provides an effective alternative.

In a binary tree the choices increase exponentially. Two decisions discriminate four choices, four decision can identify 2^4 = 16 choices and so on. A mobile screen easily affords room for six options at a time. Such a six dimensional (or senary rather than binary) tree increases the choice process significantly: three taps can discriminate 216 activities, with four taps it could be as many as 1,296 – sufficient for the full set of HETUS codes, plus contextual and detailed discrimination of specific energy relevant sub-queries.

Every screen (except 'Home' in Figure 3a) follows the same six button layout, creating consistency throughout the interface and instant familiarity for users.

ENTRY SEQUENCE

Every entry follows the same sequence of location, activity, number of other people and enjoyment (see Figure 4).

The level of detail requested can be tailored to the research interest. For instance, in relation to household electricity consumption, it may not be necessary to collect a great level of detail about activities at work. Doing emails at work can be reported as:

Work > Main job > Computer

Whereas at home the sequence would be more detailed to discriminate other screen uses, such as watching videos or online shopping:

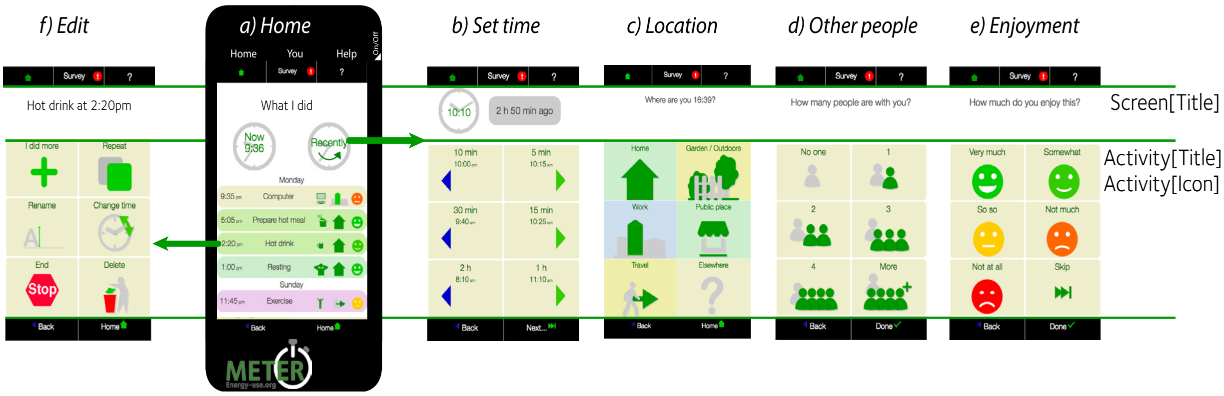

Figure 3. The Screen and Activities area with the standard 3 × 2 button layout.

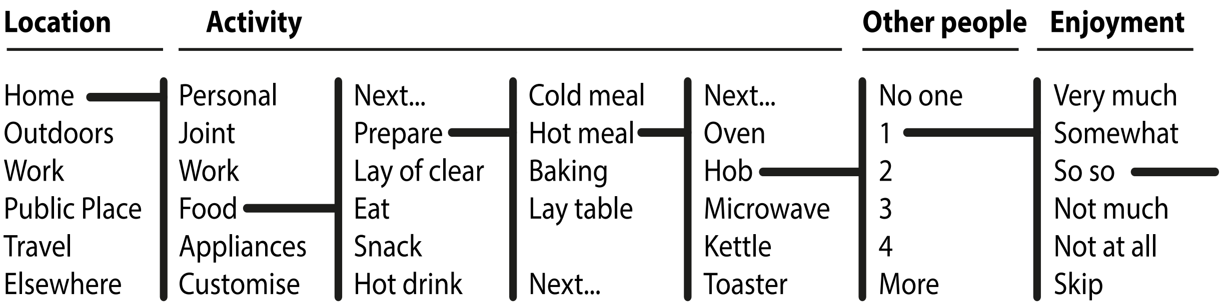

Figure 4. Entry sequence example for 'cooking at home on a hob with one other person'.

Home > Personal > Screen Time > Computer > Personal email

Activities that are of direct relevance to energy consumption, such as food preparation, can prompt particularly detailed entry sequences. In a paper diary, it is not possible to tell whether food preparation was performed with the help of appliances or not. The app can prompt for further detail. The entry:

Home > Food/Drink > Prepare Meal

will result in a screen asking to select from:

Cold meal, Hot meal, Baking, Lay Table

where Hot meal would prompt for further detail about the type of appliances used as shown in Figure 4. It is up to the user, whether to enter detail or stick with the more generic description.

In its current form the app comprises 93 screens for 590 types of activities (including some 'non activity' choices, such as location and enjoyment). From these 93 screens 4,674 choices can be made across all locations. While at home 714 choices are available (excluding "How many people were with you?" and "How much did you enjoy this?").

The choices being greater than the total number of activities is the result of multiple paths that can be taken to reach the same 'end point'. An activity can be performed in different contexts. For instance, having a cup of tea can be entered in the following ways:

Home > Personal > Time for me > Food/Drink > Hot drink

Home > Joint activity > With friends > Food/Drink > Hot drink

Home > Food/Drink > Hot Drink

The path by which the user arrived at an activity can yield important contextual information. It is thus not just the 'hot drink' that is recorded, but the context which distinguishes whether it was classified as a personal, joint or merely food related activity.

FOLLOW UP FUNCTIONALITY

The interactive nature of the app allows to dynamically engage the user. This can be used to ensure key activities are not being missed. For instance, if 'eating' has not been reported for more than eight hours during the day a message can prompt: "When did I last eat?" followed by the 'time screen' (Figure 3b). The same is possible to clarify ambiguous states ("When did I arrive home?"). Specifically relevant in the context of electricity consumption are the hours of national peak demand. These trigger a request "What I did at 5:30 pm". Tapping these take the user straight into the activity entry sequence for that time.

Follow up messages can also be used as validation tools. Asking about a time that has already been recorded is a test of consistency, or, in the case of enjoyment, a means to distinguish experienced and remembered enjoyment. Under 'Future options' we discuss additional uses of this feature.

Other than these prompts, the number of entries is left to the participant. To encourage good engagement a virtual reward scheme is included. Up to five stars can be earned and are displayed at the top of the screen. Completing the survey unlocks the first star, with extra stars awarded after 5, 10, 15 and 25 activities.

Results

EARLY DEPLOYMENT

Feedback for improvements has been collected from early volunteers who used the app in real world conditions (N = 15) as well as using it to code hand written diaries (N = 60). Continued use is likely to result in ongoing improvements and further customisation. We encourage this process through an open source platform (Grünewald (2017a)). At the time of writing the app has been deployed to over 100 participants.

Feedback suggests that participants perceive the process as a positive experience. Participation of fellow household members has increased compared to the hand-written diaries. Some participants commented that competitive recording took place, whereby people would perform virtuous tasks, such as clearing the table, in order to be able to 'claim' it in the app. Similar 'virtuous' behaviour has been systematically observed in time-use research, which report visits to the local library in excess of official visitor statistics.

Figure 5 shows a histogram of the number of activities reported per participant. The points at which stars are awarded are shown for reference. The average number of entries is 31, well exceeding the '5 star' target of 25 entries. This is a significant improvement over the equivalent paper diaries, which attract only 21 entries on average.

DATA

Two date-time values are stored for each activity. The first is time when the activity is said to be performed, the second when it was entered on the device. This difference between these two values aids as a data quality metric, which is not possible with paper diaries. For instance, the recorded enjoyment of an activity could be systematically different depending on when it was reported, as suggested by Kahneman and Tversky (2003) and Kahneman and Riis (2005).

For data analysis, a reverse process of the decision tree is needed to re-group activities into manageable sub-classes. The seven main categories shown in Figure 6 are based on an established classification (see Ellegård, Vrotsou, and Widén (2010)). These can be assigned based on activity sub categories along the users' entry path. In addition to the raw activity information, the entry path includes potentially important contextual information. Figure 6 is merely displaying a small subset of this large and complex decision space.

Figure 7 gives an extract of data resulting from this regrouping method. 1,524 activity-power pairs are displayed. This graph serves illustrative purposes only. The direct association of electricity consumption with activities is not advisable as an analytical method. Since data combines individual activities with household consumption, in many cases activities of another household member may be more directly related to load. Furthermore, activities often do not correspond to consumption at that time. 'Loading the dishwasher' is better captured through a gradient of electricity use between the preceding and the subsequent hour (when the dishwasher is in operation).

These cautions not withstanding, the highlighted 'Recreation' category shows a concentration of this activity in the evening and also a tendency for higher than average electricity consumption. A more detailed analysis of such data will follow when the sample sizes are sufficient for statistical methods to be applied.

FUTURE OPTIONS

The motivation of this paper is to stimulate the uptake of interactive tools for time use and other 'people facing' studies. Opportunities for extensions of the open source code exist and we welcome suggestions and contributions.

Smartphone devices are sensor rich. Here we discuss some of the uses to which these sensors can be put and what needs to be considered.

- **Proximity:** we have found during our study that the category 'how many people are you with' is interpreted very differently by different people. Some count everyone who happens to be in the same building, others only those they are actively engaging with (the guidance suggests 'people

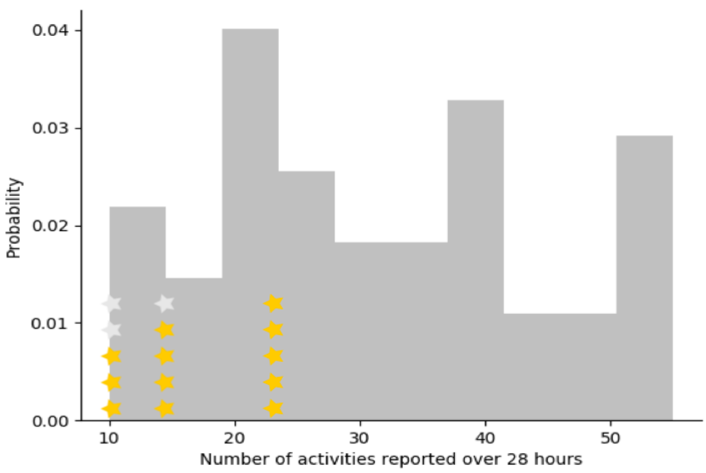

Figure 5. Histogram of activities reported. Stars award levels shown for reference. Mean = 31 entries. Participants with more than 55 entries are grouped.

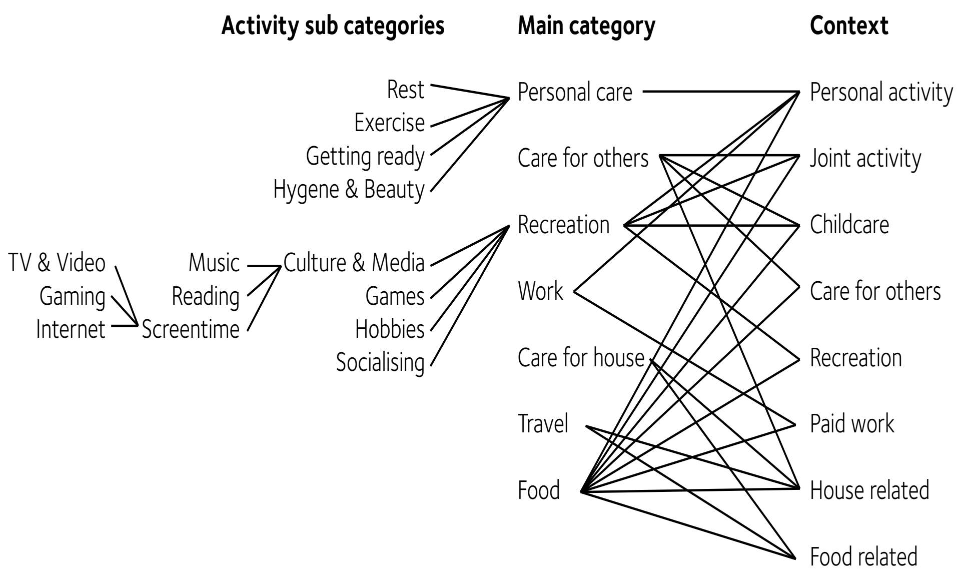

Figure 6. Exemplary elements for reconstruction of activity entry paths into contextualised categories for analysis.

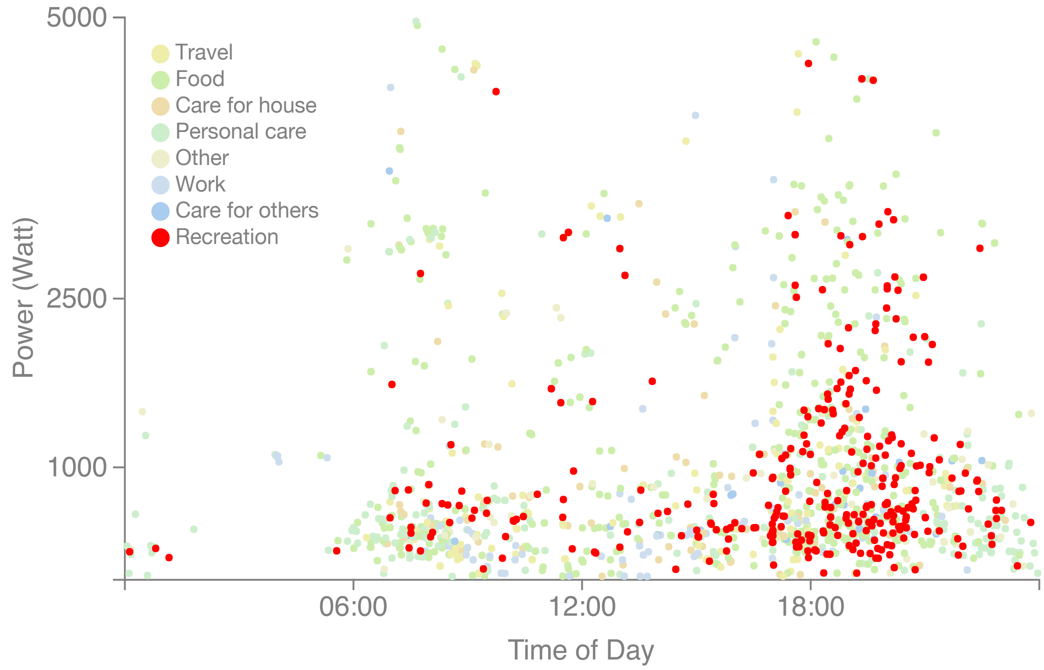

Figure 7. Correlation of main activity groups with instantaneous electricity consumption.

who are around'). Additional insights can be gained by recording device-to-device proximity. The signal strength of bluetooth, mobile and/or WiFi signals between devices can indicate who is near whom. Location can further be recorded via inbuilt GPS signals as shown by Sonck and Fernee (2013).

- **Temperature:** smartphone temperature sensors tend to be dominated by CPU temperature or the operator. Additional sensors, such as the Joulo, could reveal relationships between occupancy and activity to heating patterns (Joulo (2017)). The main challenge is consistent sensor placement for comparable results.
- **Light levels** may be more readily available from smartphone devices themselves. Light sensors come as part of the camera system. The main challenge, as with temperature, is to ensure consistent conditions when taking readings. The time when people make an entry and the device is pointing at them could be such a moment. The colour-temperature may reveal the relative contribution of natural and artificial lighting.
- **Physical activity levels** can be inferred from accelerometer data, either from an additional device, such as a wristband, or from users 'wearing' the activity recorder around their neck or in a pocket. Such data could yield valuable insights

into relationships between activity levels, health, well-being and energy use.

- **Images** can complement diaries with rich sources of information. These could either act as annotations to a reported activity, or be specifically prompted when additional information is needed. For instance, asking to take a picture of the washing machine model or state of fill. The downside of image capture is the labour-intensive interpretation (see Topouzi et al. (2016)).
- **Live electricity** readings could be used for targeted prompts to enter activities when demand is high, without necessarily revealing the trigger behind this 'random' request.

Discussion and conclusions

To better understand the patterns of electricity use and its potential flexibility we argued that the parallel collection of electricity and activity information could yield new insights. Current approaches in time-use research use paper diaries and provide limited contextual information for energy related research questions.

We have presented a novel approach to collecting activity information better suited for research alongside household electricity data. The app-based approach has been demonstrated to provide improved participant engagement and extends previous approaches in their treatment of energy relevant activities.

The principal innovations include the treatment of entries as 'instances in time', which gives activities precedence over time durations. This 'constructive time perspective' allows users to specify the time of their activities themselves and significantly simplifies the user interface to a linear entry sequence.

A second innovation is the introduction and optimisation of a senary (six-way) tree structure based on HETUS codes and further developed with user feedback. 714 types of in-home activities with contextual information can be recorded, typically with less than five screen interactions. While the user uptake and feedback has been very positive, we consider the optimisation of this complex space to be an opportunity for continuous improvement.

The app and its virtual reward scheme to encourage recordings have improved recording rates from typically just over 20 entries per diary to over 30.

LIMITATIONS

The strength of the proposed combination of activity app and electricity recordings lies in its low cost and scalability to generate statistically robust findings. The introduction of contextual information goes some way towards improving the analysis of different activity patterns and their relation to electricity. However, many subtleties and complexities of everyday life cannot be captured in this way. In depth interviews could complement the approach to enrich the understanding of underlying motivations and other factors which shape the timing of activities and electricity use.

A feature of time use research is the short participation period. This study so far only extended the 24-hour diaries to 28 hours in order to capture two evening periods. Patterns that repeat less frequently (shopping, laundry) can be difficult to capture in this way. Individual surveys are used to understand such routines, but a longer observation period may be needed for a robust statistical understanding.

FUTURE WORK

The analysis of activity and energy use information is more complex than the direct attribution of an appliance to a load. Some activities have no immediate energy impact, but constitute important contextual triggers, such as arriving home or loading the washing machine. New analytical tools are needed, building on approaches from sequence analysis and complexity science.

Once a robust baseline of activity and energy use patterns has been established, the app-based approach lends itself to interacting with participants during the study. Interventions can be used to gain a better understanding of potential flexibility of activities and observe resulting impacts on the shape of the load and activity profiles.

Such information can inform our understanding of the potential scale and contribution of demand side flexibility. It could further prove vital in designing appropriate policies and business models to realise its potential.

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Acknowledgement

This work was kindly funded by the Engineering and Physical Sciences Research Council (EPSRC) grant EP/M024652/1.