Measuring the relationship between time-use and electricity consumption

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Abstract
Much hope rests on our ability to reduce, avoid and otherwise manipulate energy consumption. In order to do so, it would be important to understand what we use energy for. Despite the early signs of 'big data' arriving from smart meters and other electricity consumption studies, very little is know about what the resulting demand profiles represent in terms of activities 'behind the meter'. This is especially problematic for peak demand periods, which could increase dramatically in coming years due to changes in technology and practices. The lack of activity based energy data has two main reasons. First, until recently it didn't matter. Under the 'predict and provide' paradigm the actual service provided by energy is inconsequential. Second, measuring at sub-meter level can be very expensive and labour intensive to instrument. Both reasons no longer apply. For demand shifting measures to be designed effectively it is essential to understand the activities (not just the appliances) involved in consumption. This paper presents a new and innovative low cost collection method that uses smart phones to collect 1 second resolution household electricity consumption profiles, while also gathering event driven activity information from household participants. The combinations of activity and consumption data bridges a disciplinary gap between social sciences and traditional engineering approaches and allows for a wealth of new insights into energy use practices. The methodology builds on established time-use research approaches, which can produce statistically significant results on the temporal relationship of activities (e.g. cooking, washing, resting) and electricity consumption profiles. The paper further illustrates how demand responses could by analysed through such a practice-theoretical perspective. This could provide new insights into the origin of demand side flexibility and its limitations. We explore existing approaches used in household electricity models and discuss their limitations, before suggesting a concept for a new approach and its possible applications.

Introduction
When it emerged during 2014 that UK electricity consumption had fallen to its lowest level since 1998 (MacLeay, Harris, and Annut 2010), despite a return to growth in the economy (Figure 1), much speculation erupted about the possible causes (Harrabin 2014). So far UK demand reduction had largely been explained with weak economic activity. Previously, the dislocation of manufacturing to Asia and the adoption of a 'service economy' had also provided a compelling rationale for lower energy intensity.

This time, however, new explanations are needed (Figure 2). Is demand reduction the result of UK policy? Is it a response to rising energy bills? Have consumers adopted more frugal energy use practices during the recession, which now persist? Are their appliances so much more efficient? Or could the record temperatures have a role to play beyond their impact on heating demand?

Which of these factors play a major, which ones a minor role? Despite the central role which energy plays in the political debate, few data are available to support or dismiss the various theories proposed.

Each explanation also has its critics. Recent UK efficiency policy (the "Green Deal") received little uptake. Consumers struggling with their energy bills, were not advised to reduce

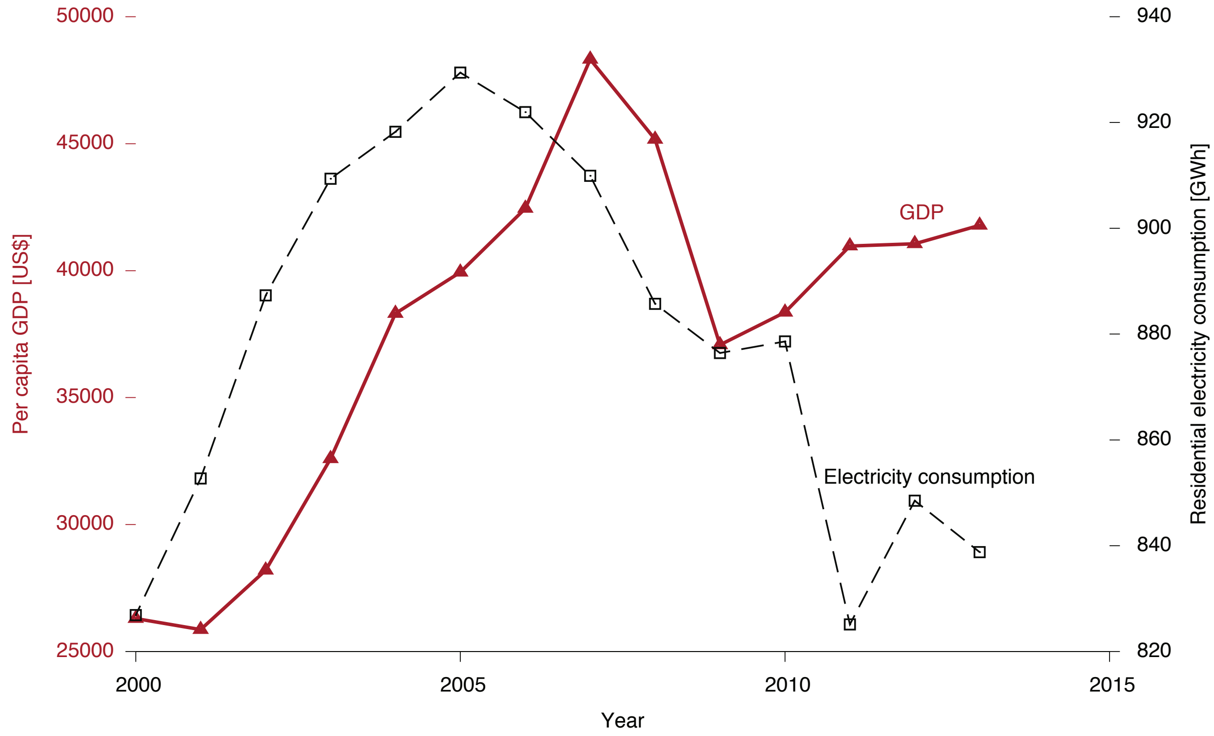

Figure 1. Residential electricity consumption in the UK fell, despite GDP growth since 2010.

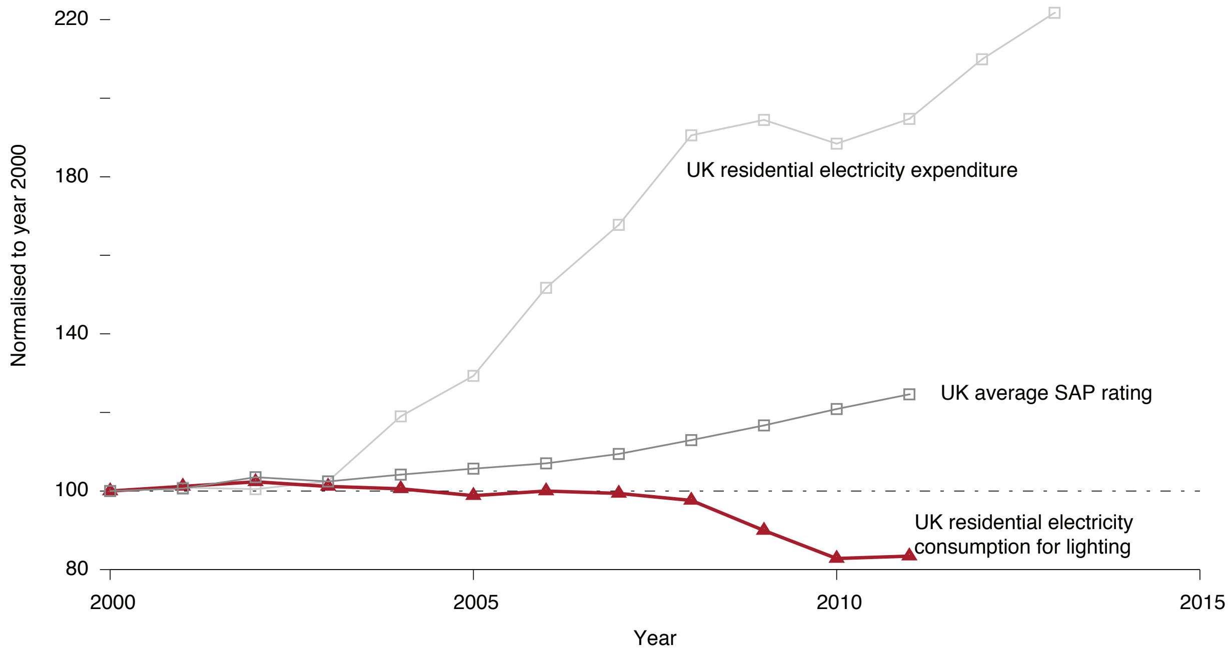

Figure 2. Possible factors related to demand reduction in the UK residential sector. Values based on J. Palmer and Cooper (2013) and MacLeay, Harris, and Annut (2010).

consumption, but asked to 'shop around' for the cheapest deal. And efficiency measures have long been suggested to trigger rebound effects, said to undermine part of their savings.

In times of 'big data', one would expect that at least after the facts, some evidence based conclusions can be drawn about the realised energy reduction. Sadly, that is not the case. First, we will discuss why we know so little about what happens 'behind the meter' and then we review some of the approaches taken to date and critically reviews their limitations. After that, we will suggest a new approach that combines hitherto independently collected data on household activity and electricity consumption, which is about to be trialled. Lastly, we argue that this approach could yield important evidence for the above questions.

Why is so little known about electricity uses?

Three factors may contribute towards the reasons why relatively little is known about our electricity use practices. Each one is briefly outlined here.

HISTORICALLY THE TYPE OF USE WAS IRRELEVANT

For decades the precise use of electricity was of no concern to system operators or policy makers. So long as the total consumption can be predicted and delivered, it is irrelevant whether this electricity is used for lighting, a dishwasher or a life-support device. The 'predict and provide' paradigm is now being challenged by the need to understand demand for a number of reasons. The emergence of renewable sources of electricity calls for a better understanding of the timing of consumption, such that certain loads could potentially be shifted to times of abundant (and therefore cheaper) electricity generation. Effective and evidence based demand reduction policies also require more detailed insights. If low energy lighting initiatives, for instance, are to be justified based on their impact, it is important to know how much of total demand is used for lighting, how new lighting technologies impact upon lighting (and other) practices in the homes, and what the time signature of these uses is. The latter is especially important in the context of peak demand, which also has fallen in the UK, and more efficient lighting is very likely to have played a major role in this transition. New and emerging practices surrounding for instance mobile devices or electric transport could profoundly change the shape of the load curve. Anticipating such changes requires detailed data to support modelling work in this area.

COLLECTING HIGH RESOLUTION APPLIANCE LEVEL DATA IS EXPENSIVE

The Energy Saving Trust performed a detailed study gathering appliance consumption data for 26 households and a further 25 on a rolling basis over one year. This undertaking required engineers to install equipment throughout the homes of participants and for scientists to conduct detailed surveys. The budget for this study was £850,000 and provided unprecedented and valuable insights (Zimmermann et al. (2012)). However, the sample size is too small for extrapolation with statistical significance at the national level. Longitudinal studies are therefore also limited in scope, unless the cost and complexity of data collection can be reduced and their reach substantially increased.

ELECTRICITY CONSUMPTION PROFILES ARE SENSITIVE INFORMATION

Although vast amounts of smart meter data are collected from over one million households in the UK, the data is not widely available for research purposes, due to the personal nature of such profiles. In the UK, smart meters are installed by suppliers and the collected data cannot even be disclosed to the relevant distribution network operators without the explicit consent of households. In most cases this consent had not been sought, limiting the application of the data.

Even if smart meter data became available for research, the section 'Combining time-use and electricity consumption' will argue that the 15 to 30 minute resolution readings yield limited insights into the household activities and changes in practices, without complementary data.

The following section will explore how, despite these inhibiting factors, energy, and more recently electricity consumption has been analysed in the past. The insights of these models support research, policy and system operation.

Household energy use models

BREHOMES

The Building Research Establishment (BRE) developed an early model of the UK housing stock, primarily with the aim to understand space heating and hot water consumption (Shorrock and Henderson 1991). The original model distinguishes between 4 age groups, 17 house types, 3 types of tenure and the presence of central heating. '10 representative patterns' are 'pre-defined' and claimed to adequately reflect the differences in 'heating patterns' resulting for 'physical and social reasons'. The underlying BREDEM model performs the energy calculation, which is summed up across the categories by frequency of house types.

The energy consumption is the product of the following components:

BREHOMES:

Energy consumption = House type × technology × demand type

DECADE

The early BREHOMES model produces aggregate consumption for individual house types. One of the first serious attempts to disaggregate electricity consumption by appliance was conducted by the DECADE project in 1994, which based its approach on the DEFU (Research Association of Danish Electric Utilities) ELMODEL developed in response to the 1970s oil crisis (Boardman et al. 1994, Boardman et al. 1995).

The bottom-up approach is based on sales data, ownership, unit energy consumption, normal distributions of lifespan and usage patterns. Heat and water usage builds on the BREHOMES model. Electricity consumption is simulated for each of the 43 domestic appliance categories. The underlying model is built on the premise that energy consumption is the product of ownership and specific appliance consumption.

DECADE:

Energy consumption = Ownership × product consumption × use factor

The DECADE project introduces a temporal dimension as well. The turnover of appliance stock is simulated, based on data from the preceding 25 years.

CREST

The CREST model from 2007 is another advance in sophistication and includes first recognition of 'energy-users' in the form of occupants. It incorporates not only the stock of appliances and their performance ratings, but adds probability distributions for the likelihood of occupancy at different times of day and also the probability of given appliances being used when occupants are at home. Furthermore, seasonal light and heat requirements are accounted for. Thus, temporal resolution is intra-seasonal for light and heat demand and simulations for individual appliances can result in profiles with 1 minute resolution (Richardson and Thomson 2007).

CREST:

Energy consumption = Ownership × occupancy × product consumption × use probability

CRITIQUE OF EXISTING BUILDING ENERGY MODELS

As these non-exhaustive examples show, considerable developments and improvements in sophistication have been achieved. All of these models are strong in their representation of the physical stock and its impact on total consumption. However, the link with the use of appliances tends to be reverse engineered. That is to say, the models are 'calibrated' against observed total consumption, such that the 'use factor' brings the model in line with this target value. Without primary data supporting the distribution or relationships between different uses this can lead to two types of error: 1) the relative weight given to different appliances may be inaccurate. Some of the use attributed to lighting may for instance be caused by televisions instead. Data to support the deemed assumptions is often based on very small samples of 40 households or fewer. 2) Aggregated values commonly disguise distributions and clustering effects. Electricity use is highly diverse. It is diverse between households (see Figure 3), but also for the same household on different days. Typical use factors based on national averages are therefore unlikely to represent very many 'typical' households.

All of the models discussed above separate the 'appliance' from its 'use'. Appliances are counted and categories and the model subsequently apply a 'use pattern', which is believed to be representative of the consumers on the bases that the model itself is calibrated against known national demand. Simple metrics to place households into categories with particular use patterns have so far not yielded strong validity, despite the use of '10 representative patterns' by BREHOMES and many similar attempts. Even simple differentiations like 'high consumption/low consumption' households do not relate to a consistent set of use patterns (RAND 2012, Fell and King 2012). The complexity and diversity of energy uses makes any generalisations a formidable task (for a discussion of the resulting uncertainties, see Hughes et al. 2013).

Shipworth (2013) argues that demand models overemphasise the building fabric and appliances, while poorly representing the occupants. In fact, the term 'occupant' reduces people from a complex social agent, to a boolean variable (at home/not at home). More detail may be required if their role in electricity consumption is to be better understood.

Furthermore, the appliance stock at the time of the DECADE model was modest compared to today. Appliances have a higher turnover and defy conventional classification (mobile phones for instance have merged the functionality of many devices). The historical data used in the DECADE model spans the preceding 25 years. In the subsequent 25 years household

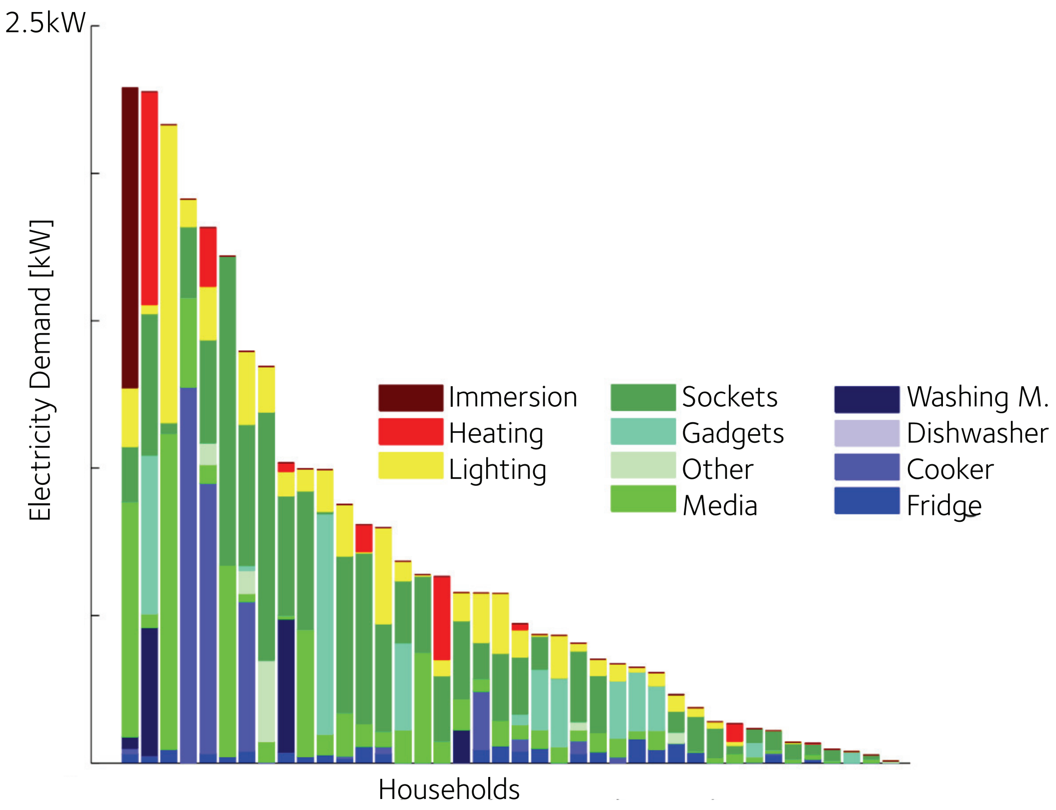

Figure 3. The diverse distribution of household electricity uses during peak demand makes generalisations more difficult. Data based on EST (2012).

appliances and their uses have changed beyond recognition. More dynamic and longitudinal data collection methods are therefore required, if such transitions are to be captured and their future impact anticipated.

Combining time-use and electricity consumption

The previous section argued that primary data is lacking to link the use of energy services at the individual level with the consumption of appliances. Furthermore, in the face of ever faster changing appliance technology and the co-evolution of new practices (e.g. on demand television on individual mobile devices) static models of household consumption fail to capture longitudinal trends and shifts in energy use.

This paper therefore argues that a sufficiently low cost data collection approach is required that captures energy consumption in parallel with activities. This approach must be scalable to statistically significant sample sizes and should be suitable for longitudinal repeat observations over decades.

Household activities and electricity consumption are already collected using well-developed methods. However, two fundamentally different approaches are used by social scientists (seeking to understand time-use of a population) on the one hand and energy researchers (wishing to explore a population's consumption of energy) on the other. Both approaches will be briefly outlined, before proposing a mechanism to combine them.

TIME-USE RESEARCH

Time-use research is based on diary information collected from a large sample of individuals. The full scale 2000/01 UK Time-use survey (TUS) collected 21,000 diary days, while the smaller follow up study in 2005 still collected 5,000 (Lader, Short, and Gershuny 2006). Participants provide information about their activities with 10 minute resolution in hand written diaries. These entries are subsequently coded by categories set out by the Harmonised European Time-Use Surveys (HETUS) to allow comparisons between EU member states, as well as to explore longitudinal trends (eurostat 2014). Importantly, participants are only asked to provide one or two days of diary information. This ensures that participation is not too onerous and that response rates and reporting accuracy are high. Since the variability between days can be significant (both for day-to-day activities and for energy use) it is important to sample sufficiently large numbers of participant days, such that these studies provide evidence that is suitable to support policy development (Gershuny and Sullivan 2003). The abovementioned studies meet this criterion by collecting well in excess of 2,000 diary days. In addition to the day-to-day variability, sample sizes need to capture socio-demographic distributions, especially if sub-groups, such as the elderly of fuel poor, are to be captured in sufficient numbers to conclude on differences between them and the general population.

ENERGY-USE RESEARCH

In energy research, consumption data collection generally follows a different approach. The Irish Commission for Energy Regulation study is one of the largest of its kind. It sampled total household electricity consumption for around 1,000 households in 4 different time-of-use tariff groups and one control group of similar size for over one year (CER 2011).

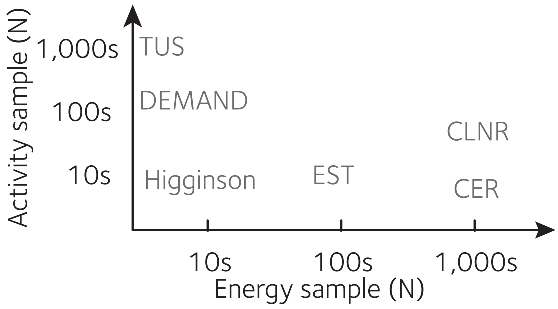

Figure 4. Studies tend to focus on either large sample sizes for activities or electricity data.

The Ofgem funded Consumer Led Network Revolution (CLNR) also collected time resolved electricity use profiles, comprising a sizable control group of over 8,000, who where metered, but not intervened with. The qualitative research captures 131 domestic participants and appliance data are collected for fewer than 100 households (Bulkeley et al. 2014). The Household Electricity Survey (HES) equipped 251 homes with appliance level meters and monitored these for between one month and a year. Information about behaviour and practices is collected via questionnaires for a small subset of participants (EST 2012).

As Figure 4 illustrates, sample sizes for activities underpinning energy consumption tend to be orders of magnitude smaller than the energy data samples by CER (2011) and Bulkeley et al. (2014). This is in large part due to the complexity and cost of instrumentation, but means that many recent studies have to rely on extrapolation from small sample sizes (for instance: 72 households (S. Firth et al. 2008) or 30 sample days (Terry et al. 2014) to elicit national consumption patterns.

SAMPLE SIZE REQUIREMENTS

How large would a sample need to be for it to become statistically significant and allow differences in energy use to be attributable to correlating factors? For energy consumption based research to deliver policy relevant evidence, it must be scalable to the national level and have sufficient resolution, such that the effect of interventions can be separated from unrelated influences.

In the absence of robust data, an 'order of magnitude' approximation can be made with some simplifying assumptions. As a minimum requirement the confidence in the mean values collected should have an accuracy (ε) of five per cent or better to ensure any significant demand contributions are captured. The confidence interval for these data should at least meet the scientific standard of 95 % (two standard deviations). The mean (μ) of UK household electricity consumption is on the order of 4,000 kWh per annum (DECC 2014), with a standard deviation (σ) above 3,000 kWh, resulting in a Coefficient of Variance (CoV) of around 0.8. The Wald method for binomial distribution[1] can be applied under these simplifying assumptions:

1. Power laws could also be applied. Given the lack of knowledge over the actual distribution of individual energy uses, this method provides merely a rough indicator.

$$N = \left(\frac{1.96 \times \sigma}{\epsilon \times \mu} \right)^2$$

which suggest a minimum sample size of around 1,000. This is very much an 'order of magnitude' estimation of the lower bound, due to the simplifying assumptions above. In practice, demand is not normally distributed and individual end uses may follow more complex distributions. During peak demand – a period of particular interest for this research – the aggregated CoV for households has been found to be around 0.5 (Bulkeley et al. 2014). Yet the distribution of sub-loads is higher than the aggregated total. As the peak-demand snap-shot of 42 homes in Figure 2 and research by Morley and Hazas (2011) suggests, the variation of appliance uses is higher and thus requires larger sample sizes. A sample size of 2,000 would be sufficient for a CoV of up to 1.14. Only once the relevant data has been collected can one assess which types of loads may require larger samples to yield statistically robust results due to very high CoV values.

While time-use studies with sample sizes in excess of 2,000 participants exist, most energy use research has to contend with smaller samples to date. This imbalance may, at least in part, be related to the relative costs of administering diaries and installing energy data collection equipment.

COMBINING TWO METHODOLOGIES

Combining time-use and energy-use research can yield a number of mutual and wider benefits. This section sets out how this may be achieved while at the same time significantly reducing the cost of data collection. First attempts to combine time-use and energy-use information from secondary data are undertaken by End Use Energy Demand centres in the UK, notably DEMAND, who use the Trajectory Global Foresight time and location data of 500 people to explore activity sequences and mobility patterns. However, the primary data on time use and energy consumption is collected independent of each other, making it harder to establish the links between the two. Spataru and Gauthier (2014) also use SenseCam information and relate it to thermal comfort and electricity consumption. However, sample sizes remain small.

Significant intelligence can be gained from the parallel recording of activities and electricity use and some of their individual shortcomings can be mitigated. For instance, reporting biases, which are known about in time-use studies leading to potentially under- or over-reported activities, such as hours of TV time, can be calibrated based on the insights from electricity consumption profiles, thereby improving the accuracy of time-use studies themselves.

The main advance over conventional energy monitoring approaches is that the electricity use profile can be attributed directly to energy uses. For demand response research this may be more relevant than appliance level consumption.[2] It is commonly accepted that consumers do not use energy, or even appliances for their own sake, but for the energy services they provide. Practice theory goes further and suggests that the agency lies with practices themselves – culturally established norms that are 'enacted' by individuals (Shove, Pantzar, and Watson 2012). The applicability of different behaviour models is characterised by Chatterton and Wilson (2014). The latest UK research applies practice theory to understand energy use and its flexibility in response to requests to shift demand (see for instance Higginson, McKenna, and Thomson 2014).

By understanding the temporal links between practices (for instance 'washing': the sequences of preparing laundry, washing, drying, ironing and handling), secondary activities, and the surrounding triggers and constraints (clean clothes for sports event, meal times, appointments), a new perspective for our understanding of the scope and effect of changes to energy use profiles can be gained, which moves beyond the implied agency of appliances using energy autonomously, and broadens the lens to capture what this energy is used for. This insight makes subsequent analysis more robust towards changes and transitions in practices, which are in part influenced by appliances, but can have a variety of other causes, including household composition, health, social norms and socio-economic conditions.

Analytical tools for the combined assessment of time use and electricity consumption data have been developed by Ellegård, Vrotsou, and Widén (2010). These allow to visually assess sequences and correlations between activities and electricity consumption (Ellegård and Palm 2011). However, for statistically robust conclusions, large samples, collected simultaneously are not only desirable, but essential.

PRACTICAL IMPLEMENTATION

With time-use studies already collecting sufficient sample sizes using hand written diaries (Lader, Short, and Gershuny 2006), approaches to reach equivalent samples sizes of electricity use profiles are required. Smart-meter deployment may provide such data in future, such that no additional installations are required. For this approach participant consent and access to the data need to be negotiated. Despite the UK government's intentions to make such data available (DECC 2012), present difficulties experienced by the research community and other stakeholders (such as distribution network operators) to access existing smart meter data in the UK, suggest that both privacy and technical issues still need to be overcome. Furthermore, deployment levels are presently still too low and regionally confined. Limiting trial participants to households with smart meters would therefore be substantially restricting the sample selection. Furthermore, smart meter data is typically resolved to 15–30 minute samples, which may not always be sufficient for the level of the interpretation attempted here.

OPTION 1: ELECTRICITY USE COLLECTION ALONGSIDE HAND WRITTEN DIARIES

Instead, low cost smart-phones have been developed (Layberry 2014) and reconfigured to act as low-cost, high-resolution electricity meters (Figures 5 and 6). The microphone port is connected via simple electronics to a current clamp. The system can capture electricity consumption with high temporal resolution (1 second) and sufficient accuracy to detect changes in consumption (<5 %).

2. Some appliances with characteristic signature profiles, such as fridges or dishwashers, can be disaggregated to some extent, due to the 1 second resolution of the profile data. Disaggregation accuracy can be enhanced when used in conjunction with activity information.

Key to its application is the ease of installation and use of the meter. It can be sent to participants in the post, alongside the diary, with visual instructions for installation, as shown in Figure 5. Once 'clipped' to the mains, the meter will switch itself on at midnight of the pre-specified diary date and begin recording and storing data on battery power, while participants document activities on the day in their diary (Figure 6). Diary and meter are returned by courier, data is downloaded and coded up, before the same equipment can be redeployed in the next household. Participants have minimal engagement with the meter. The unit shown in Figure 5 is packaged as a black box with no settings, connections (other than the clip) or buttons. This minimises the sense of 'being monitored', which could affect behaviour.

OPTION 2: ENERGY TRIGGERED DIARY COLLECTION

The use of smart phone technology opens up further opportunities for innovation in the data collection. Hand written diaries are onerous to fill in and may lead to errors and loss of information when attended to long after the events, as is often the case with participants completing the diary in the evening.

Instead diaries themselves can be collected with smart phone technology (Figure 6). This brings about several benefits over paper diaries.

1. The software can propose a shortlist of activities based on their likelihood at certain times, following previous activities or other socio-demographic factors (e.g. number and age of children). Participants are prompted to select from this list, reducing the effort of entering information to an average of three taps (Harmonised European time-use codes are structured into three hierarchical levels – see eurostat 2014). The exact time is recorded automatically, unless the entry is backdated by the participant.
2. While free-form entries can be submitted, the pre-coded activities no longer need to be read, interpreted and 'coded up' into time-use codes by researchers after the trial.
3. Several individuals within one household can provide information on the same day. The signal strength between phones provides an indicator of relative proximity between participants (for example to establish whether a TV watched by one, two or three people jointly).
4. Further ancillary information can be collected using sensors, which are standard on most budget 'smart' phones: GPS (location), accelerometer (activity level), microphone (noise level), camera (light level or photos for easy illustration of activities and appliances). A temperature sensor has also been developed for use with the microphone port.
5. Diary collection events can be concentrated on the most relevant periods, depending on the research question. Partici-

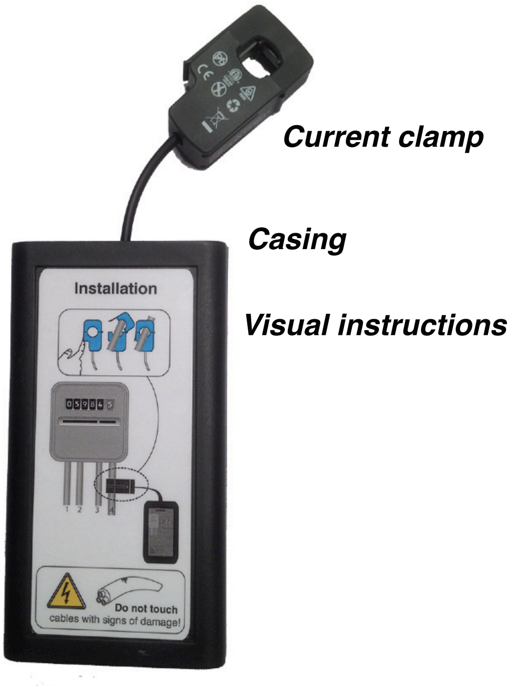

Figure 5. The smart-phone based device is fully cased. Instructions explain how to install the current clamp beneath the electricity meter. Participants do not have to make any other settings or connections.

Figure 6. Illustration of one day parallel collection of electricity and activity information. Smart phones significantly reduce the burden on participants (option 2) and support 'response mode' operation (option 3).

pants, who are not near the home, need not be promoted for responses, as they do not contribute to electricity consumption. Conversely, peak demand periods (winter weekdays between 5 and 7 pm) can be given priority for more frequent prompting to enhance data quality at these times.

6. The timing of response triggers can be set to specifically collect activity information at times of high electricity consumption or to explain use profiles that are otherwise difficult to disaggregate.

This range of benefits, with point 6 in particular, significantly reduces the impact of data collection on participants, while maximising the relevance of the collected data for specific research questions.

Additional sensing could include gas boilers and cookers. Temperature, humidity and light sensors or longer collection periods (>1 day) could further enhance the explanatory power of the data.

OPTION 3: FEEDBACK MODE AND RESPONSE ASSESSMENT

A strong motivation for this research is a better understanding of demand response options and the development of models to assess the scope for load shifting and its possible impact. For this it is important to investigate the participants response to 'signals' aimed at altering the consumption pattern. So far, the only sizable studies have focused on time-use-tariffs as the signal, and measured whole house consumption as the response (CER 2011 or Bulkeley et al. 2014). Evaluating different forms of signal and a more detailed study of the mechanisms by which the response is provided are desirable.

Signals could include static tariffs as well as short term incentives (penalties or rewards), and specific requests, information and feedback grounded in behavioural economics.

At what times and under which conditions are such requests likely to yield the desired response? Which signals are most effective and do these differ by user type and response sought. Response types could include the length and depth of response sought, the regularity and frequency with which requests are made, the warning period and the urgency/value of the intervention.

The above methodology is ideally suited to inform these research interests with evidence. The method used for the diary collection opens up opportunities for expansion to test theories on participant response. Alongside diary information requests, participants receive messages to influence their activities at relevant times. Messages could suggest high electricity prices for the next hour, offer a reward for reduced load, or use socially motivated triggers and nudges. More innovatively, messages could alert participants and suggest a change to current activities from a selection, based on the intelligence gathered about the energy uses practices.

The actual response can be observed both through the consumption profile and via follow up messages interrogating the subsequent activities. This information, especially in conjunction with the previously established baseline data on consumption profiles, could be used to test theories on the most effective means to encourage load shifts and provide valuable insights into the dynamics, scope and barriers to demand response and changes in energy use patterns.

The scale at which the above method allows this research to be carried out, can deliver statistically robust results and detailed background information about 'how' demand responses are delivered and how this impacts on other practices, including potential 'bounce-back' effects, whereby suspended demand could lead to a higher load after the request period.

LIMITATIONS

The primary motivation for the above procedure is to minimise complexity and cost in order to allow large sample sizes to be collected. However, this approach has some limitations.

The collection of only one day of data per participant obscures patterns that have lower frequencies than one day. For instance, routines around clothes washing or grocery shopping cannot be captured by taking one day samples. The benefits of extending the duration needs to be weighed up against cost of collection and the cost (i.e. effort) for participants. These costs are likely to be lower for electricity readings, than for diary collection.

No appliances are monitored individually and the disaggregation approach has limitations in its ability to distinguish steady or unusual loads. This paper argues that the activities themselves should be the focus of enquiry. However, for some areas of research specific appliance data is important. For these, additional 'smart plugs' may need to be deployed, which adds to cost and installation complexity.

Contextual data is required to complement the diary and consumption data. These need to be collected through surveys and capture socio-demographic as well as building and appliance stock information. The questionnaire can also be administered via the smart-phone app.

A major cost saving over conventional data collection approaches is the absence of a personal visit for installation and interview. This can lead to low uptake, faulty installation and mistaken responses. Initial deployment with personal visits will seek to establish the most common issues and address these with simple and clear instruction material.

Conclusions

This paper has argued that the data underpinning present household electricity demand models is insufficient to meet the need for detailed insights into the composition of electricity uses and the underlying activities. It is therefore unfit to provide answers to some of the central questions of evidence based policy making on energy demand, including the causality between efficiency policies, energy prices and consumer behaviour on overall consumption.

A deeper understanding of 'what electricity is used for' is becoming increasingly important, as efforts to reduce demand and the need to integrate intermittent renewable sources of electricity becomes more pressing. Current data collection approaches have been identified as too costly for mass deployment. This has limited the scale at which data collection is conducted, resulting in many studies not meeting the minimal sample sizes required to yield statistically robust information as set out in this paper. Better and cheaper data collection approaches are needed to construct meaningful baselines. Such detailed baselines are essential for evidence based policy support of demand reduction and demand shifting.

One such data collection approach has been proposed here, which combines the collection of time-use information with detailed electricity readings at the household level. The instrumentation and data collection methodology promises to improve on the insight gained from their collection in separation, reduces the cost of collection and minimises the burden on participants.

The interdisciplinary collaboration between hitherto unrelated areas of research in sociology and engineering may thus prove to yield important building blocks for the advancement of insights into the socio-technical complexity of energy demand.

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