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The electricity footprint of household activities - implications for demand models

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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.

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]. Grünewald 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.

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Tabel 1
Selected characteristics of study participants. National figures based on ONS [16], ONS [13], ONS [14], ONS [15] and UKERC-EDC [25] data.

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. 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.

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 Grünewald 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