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The specific contributions of activities to household electricity demand

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ABSTRACT

In this paper we present new methods to collect and analyse household activity and electricity consumption data. We show how such data can be used to establish relationships between activities and electricity consumption in two different ways. First we create direct associations between activities and the electricity demand at the time. This electricity footprint gives an insight into the typical load intensity of an activity, which can include other activities that are commonly performed in close temporal proximity.

Our novel contribution is the concept of *marginal electricity demand* which can be attributed to specific activities. To disaggregate and approximate the loads for such an activity, we present a new regression approach. The marginal demand of an activity is based on its relative load contribution to any other activity within a collection of over 18,000 activity pairs.

Meal types stand out as clearly distinguishable activities. Hot meal related activities show some of the strongest positive contributions to demand, whereas cold meals tend to reduce demand at the time of reporting. Activities such as a hot drink can lead to an overall reduction in demand at the time, despite their direct energy consumption.

The potential of this marginal metric will be discussed as a new way to understand energy service demands. Unlike conventional attribution of demand to appliances, it is possible for activities to have a negative marginal demand. This opens up new opportunities to conceptualise the meaning of energy service demand and approaches to encourage demand reduction or shifting through positive actions.

1. Introduction

The UK has committed itself by law to become a net-zero carbon emitter by 2050 [1]. It is the first major economy to take this step. To achieve this ambition both supply and demand may have to undergo fundamental changes. Security of supply in a deeply decarbonised system can become increasingly costly [2]. New solutions are required to ensure important energy services remain affordable.

The cost of supply-side decarbonisation is fundamentally a techno-economic question, whereas our willingness to adopt new and potentially lower standards in the reliability of provision touches on complex areas of social practice, norms, equity, justice and political economies.

New technologies and efficiency measures will play an important role in easing the transition towards new systems of provision, such that service provision can be maintained or improved [3]. However, in some areas service expectations themselves may need to change or even be reduced [4,5]. Such transitions away from indulgent behaviour patterns are not unprecedented. Smoking and more recently attempts to reduce single use plastic suggest that some publics do support measures that reduce their own consumption. For this to be successful in the energy sector, some commentators have suggested that the ‘invisibility’ of energy use needs to be addressed [6,7]. This applies to energy users, as well as policy makers and other stakeholders who at present have limited visibility of energy service demand ‘behind the meter’.

While increasingly rich and “big” data are being gathered about electricity loads and higher spatial and temporal resolution [8–10], little is known about the energy services and social functions these loads serve.

Some studies have attempted to measure energy use at the appliance level [11,12] or infer uses from load data [13,14]. Others assess potential demand side flexibility with time-varying prices and observe changes to load profiles [8,9,15].

Energy service demand is not necessarily the result of spontaneous economic decisions made at individual level, but can be the result of social norms and practices [16].

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Load profiles can give some insights into practices, but even with demand disaggregation of appliances, it is not always possible to understand which social functions these appliances fulfil [17].

Time-use data have been suggested to explain the patterns in energy demand. They are used to model demand profiles and explain changes in demand [18–21]. Active occupancy and specific activities reported in time-use surveys are used to build bottom-up load profiles. However, the relationship between activities and their coinciding demand has not been explicitly measured [22,23]. Instead, assumptions have to be made about the type and demand of television sets in the population and that these are in use when (and only when) 'watching TV' is reported in a time-use diary. Furthermore, time-use codes were not designed for energy related questions and often lack critical distinctions. Activities like *Meal preparation* can have very different energy demands depending on the time of day they are being reported. With current data it is not possible to tell or discriminate the difference between a cooked meal and a cold one. Use of appliances is often not explicitly included and preparation of a hot drink does not have a time-use code [24].

We therefore propose an approach that bridges this gap through the concurrent collection of dedicated household activity and electricity consumption data. The approach presented by [17] concluded that for greater discrimination of the electricity footprint of activities new categorisation and regression techniques may be required. This paper builds on [17] and presents a more refined approach to grouping activities and techniques to attribute loads in a way that results in improved discrimination.

2. Method

2.1. Data collection

Data for this analysis is the UK Household Electricity and Activity Survey (2016–2019) [25]. The sample is a convenience sample, recruited with the help of press coverage, radio appearances, promotion at public events and on social media. No explicit rewards are offered, but each year one participant can win the cash equivalent of their electricity bill for the past year.

Selection biases apply and have been discussed by [17]. Table 1 summarises some of the socio-demographic misrepresentations in the sample. High income households, PV and EV ownership are significantly over-represented. For some forward looking enquiries, the high share of EV and PV can be beneficial to understand their impact on load and activity patterns. However, these are relatively early adopters and therefore not necessarily representative. Rented accommodation is under-represented, despite efforts to reach out to these groups. Many residents in rented accommodation report not to have access to their meter and therefore cannot participate.

Table 1
Selected characteristics of study participants. National figures based on [26–29] and [30] data from [17].

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
Statistics of the METER data deposition March 2019.

Property	Records
Earliest record	17 Feb 2016
Latest record	18 Jan 2019
Households registered	414
Households participated	361
Distinct households	293
Electricity	
Complete electricity records	264
Electricity readings (1 minute)	596396
Electricity readings (10 minutes)	60085
Activities	
Activity recorders issued	743
Activity records	529
Activities reported	16378
Paper diaries	134
App based diaries	395

Table 2 summarises the data used for this analysis. The data and full documentation are available at [25]. In addition to the electricity and activity records analysed here, the deposition also contains valuable socio-demographic information about the household and personal characteristics and preferences from a survey of each individual household member. Furthermore, every activity record contains information about how many people were involved in the activity and how much it was enjoyed.

Electricity is recorded with a self-administered current clamp, which participants attach under their mains electricity meter. The clamp reads current off of the live or neutral lead, for the entire household load. The devices automatically record electricity with 1 second resolution for a 28 h period from 5pm on study day one, to 9pm on day two, such that the peak period from 5-7pm is captured twice. While the temporal precision is high, the accuracy of power varies by around 5% between devices and low power factors can further distort accuracy. Devices with electric motors may therefore appear more energy intensive than they are.

An electricity record is considered 'complete' if the readings have been validated and readings are consistently above 20 Watt. Some households attached the recorder shortly after the study period begins and still returned some valid data. Some of the registered households have not yet taken part, while others have done the study more than once.

2.2. Activity categorisation

The activity recording app is described in detail by [31]. It guides participants through a choice of activities with six options per screen [32]. Each household member above the age of eight is encouraged to record their activities. With three selections up to 216 activities can be discriminated and many activities allow for additional detail to be provided. Attempts to validate the accuracy of reporting have been undertaken by [17].

The choice of activities and their description has the potential to influence the results in sensitive ways. Several stages of refinement have therefore been undertaken. In the first instance activity codes are inherited from the Harmonised European Time-use Survey (HETUS). These surveys inform many research questions in the field of sociology and focus on areas such as 'caring for others' and intra-family dynamics, for which they ask detailed questions about which household members are involved in the reported time-use

[24,33]. More recently these data have found use in economics and energy studies [34,35].

In this study some activities can only be reported at a more generic level. 'Caring for others' (code 3912) may be refined as 'caring for child' (3800), but not as far as 'Helping a dependent person with a disability or illness' (3921).

Conversely, activities with particular relevance to energy consumption have additional detail that can be reported. 'Food preparation' (3110) can be refined as 'hot' or 'cold meal preparation', which can be further followed up with specific appliances used ('oven', 'hob'...). A category for *Hot drink* and several appliances (*Oven, Washing machine*,...) was added.

Activities can be reported at the time they are being performed. It is also possible to back-date or pre-record activities. Both the time of reporting and the time of the reported activity are recorded. Conventional time-use surveys take a time budgeting approach, for which the day is divided into a given number of time slices. Diaries ask participants to account for each of these time slices. The duration of the slices has changed over time from 30 minutes to 10 minutes in the HETUS. On the other hand, the METER app used in this study follows a 'constructive time perspective' [31,36], whereby participants decide themselves when to report. If participants report their current activity (by pressing 'Now' as the time in the app), times are recorded with one minute precision. Should they wish to adjust the time manually, they can do so with five minute resolution.

The app does not enquire about the duration for each activity. It is possible, but not mandatory to report the end of an activity. [36] suggests that this approach emphasis the reporting of activities that matter in people's lives, rather than the ones that take up the most time. It may therefore be telling that a *Hot drink* does not feature in the HETUS, but forms one of the most reported activities in this study.

The involvement of other people in an activity has been simplified from a detailed description of *who* else was involved (without a count) to six options for *how many* other people partook in the activity (0–4 and more).

All activities and electricity readings are re-sampled to 10 minute readings for ease of analysis. Electricity can be downsampled with relative ease. The unit of measurement is maintained as average Power (Watt) over the time period.

Clustering activities is a manual process and requires considered judgement and interpretation [17]. A total of 184 different activity codes have been reported by participants. In some cases these can be grouped without much ambiguity. *TV* (the appliance) and *Watching TV* (the activity) can be combined into a single category *TV*.

Table 3 shows an example of activities that have been grouped together under the heading 'Housework'. Arguably laundry could be included within this group. The decision how far to cluster these sub activities is partly informed by the frequency of their reporting, such that each group has a meaningful number of members. Laundry related activities are sufficiently common to be classified as a separate group.

Table 3
Classification of activities as 'Housework' and associated time-use codes (tuc).

Activity	tuc
Work or Housework	1300
Housework	3200
Cleaning	3214
Clean floors	3213
Cleaning yard	3220
Clear up	3250
Cleaning house	3211

Using this approach 178 of the most commonly reported activities have been reduced to 39 activity clusters.

Only activities performed at home are included in this analysis. Households with photovoltaics, which can affect net-demand readings, are excluded. This leaves 8236 reported activities for this analysis.

2.3. Activity attribution

For the analysis of activity related consumption [37] proposes to use de-minned power readings. The minimum demand $\min(E_H)$ for Household H, which is likely to comprise stand-by devices and other continuous loads, is assumed to be activity independent. By removing this base-load from the data, the residual load profile $E_H(t)$ has been shown to be more strongly related to discretionary activities. We establish the de-minned load (E^*) for each household (H) as

$$E_H^*(t) = E_H(t) - \min(E_H) \tag{1}$$

For each activity A we attribute an electricity footprint E_A as the average de-minned demand E^* for the associated household for the 30 minutes before and after the activity time t_A. The one hour window, centred around the activity, is chosen to cater for a range of cases. Short-lived uses, such as a kettle, could be captured within a shorter window, while some larger white goods can run for over an hour. For some activities (loading dishwasher) demand tends to occur after the activity, whereas for others their main demand precedes it (eating a hot meal). The ± 30 minute window is a compromise to accommodate for this wide range of activities.

The electricity footprint of an activity E_A can thus be written as:

$$E_A = \frac{\sum_{i(A)} \frac{1}{T} \sum_t E_H^*(t \in [t_{i(A)} \pm 30min])}{N_A} \tag{2}$$

where N_A is the number instances (i) of activities reported. T is the number of 10 minute periods for which electricity readings are available for the 30 minutes before or after the activity. If activities are reported in the first or last 10 minutes of the study, T can be reduced to 4 periods.

The attribution of load to all activities performed at the time is meaningful so long as activities are interpreted in their wider context. The energy attributed to *Eating a hot meal* does not suggest that eating by itself uses this amount of electricity, but rather that the wider complex of hot meals, with preparation, dish washing and other activities that are more likely to happen in the surrounding 30 minutes, give rise to higher consumption.

This overlap of activities is helpful when exploring key activities that coincide with high demand. However, there is a risk that activities that often coincide in time, but are fundamentally different in their electricity demand get blurred and conflated. To address this issue we propose the concept of marginal activity demand.

2.4. Marginal activity demand

To discriminate the marginal contribution of specific activities more clearly we perform the following approach. For each activity A the attributed electricity footprint is E_A for the surrounding ±30 minutes as per Eq. (2). During this time another activity A' may or may not be recorded. For all instances $i(A, A')$ where A' is reported within 30 minute before or after A in a Household H, the joint electricity footprint is

$$E_{A,A'} = \frac{\sum_{i(A,A')} \frac{1}{T} \sum_t E_H^*(t \in [t_{i(A)} \pm 30min])}{N_{A,A'}} \tag{3}$$

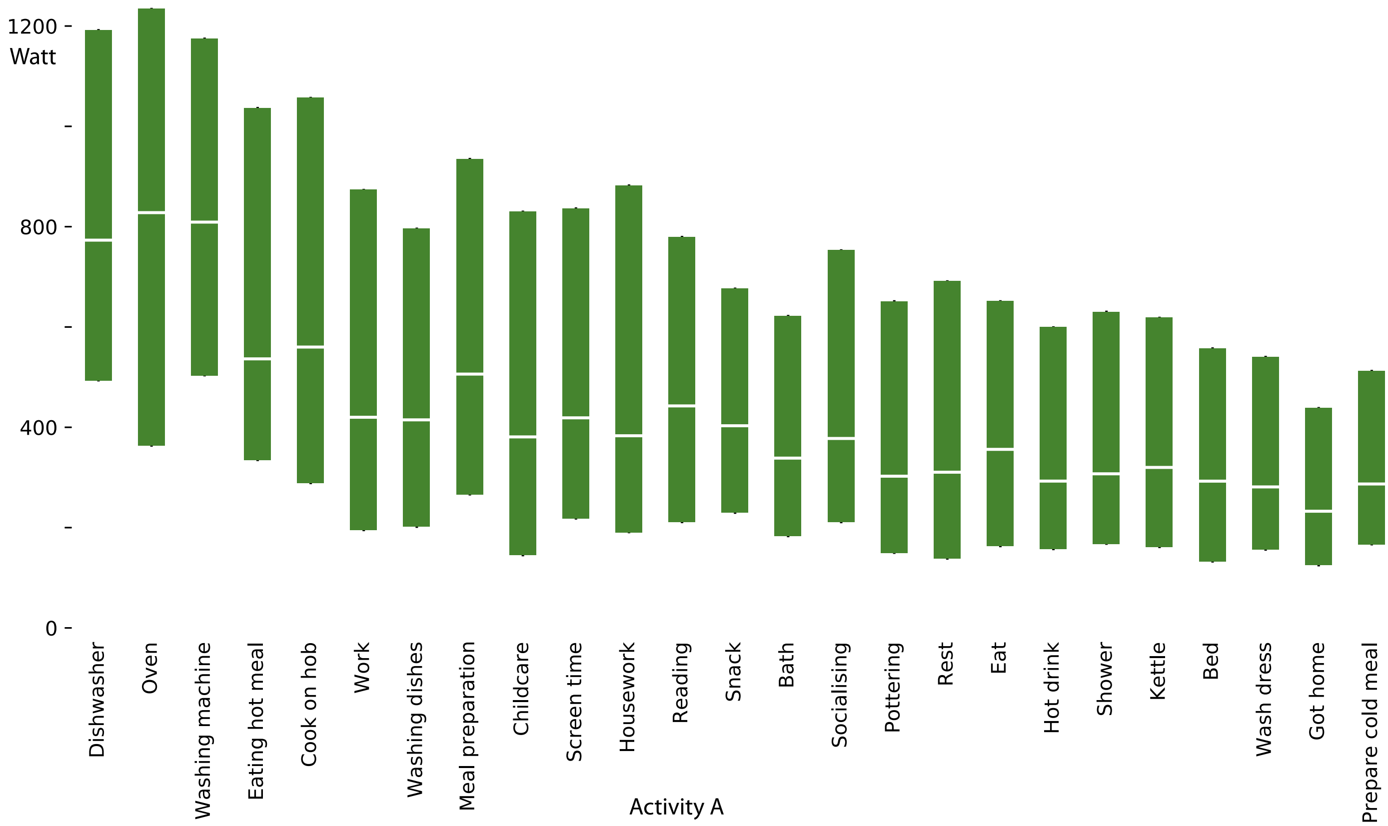

Fig. 1. Electricity demand during the hour of reporting activities.

Conversely, all instances where activity A is reported without A', we obtain a footprint as:

$$E_{A,\bar{A}'} = \frac{\sum_{i(A,\bar{A}')} \frac{1}{T} \sum_t E^*_H(t \in [t_{i(A)} \pm 30min])}{N_{A,\bar{A}'}} \tag{4}$$

The difference between all activities A with and without A' can be considered as the marginal contribution (E^*) of A' to the electricity footprint of A. This can be expressed as

$$E^*_{A',A} = E_{A,A'} - E_{A,\bar{A}'} \tag{5}$$

for each pairing of activities. Not all activities appear in pairs in the surrounding 30 minutes often enough to perform this calculation. Use of ovens rarely happen within half an hour of sleeping. For all activity pairs with a sufficient number of coincidences (A, A') and non-coincidences ($A, \bar{A}'$) a value of $E^*_{A',A}$ can be established. We limit the analysis to the 25 most common activity clusters, for which at least 100 reported activities exist.

To reduce the matrix of activity pairs to a single marginal demand value per activity ($E^*_{A'}$) the activity specific contribution can be aggregated across activities A as follows:

$$E^*_{A'} = \frac{\sum_A E^*_{A',A}}{N^*_{A'}} \tag{6}$$

where ($N^*_{A'}$) is the number of pairings with statistical significance.

$E^*_{A'}$ is thus an approximation of the specific difference the presence of activity A' makes on household electricity demand. This value should provide a closer estimation of the contribution of an activity to electricity demand than the attribution in Eq. (2). In the following section these approaches are tested with original data to assess the validity of this approach and the scope to establish relationships between activities and electricity demand.

3. Results

3.1. Activity attribution

Fig. 1 shows the 25 most commonly reported activities A ranked by the mean of their associated electricity footprint E_A. The white bars show median demands. The distributions of load observed for each group are highlighted as the bars for the ±25th percentiles.

The diversity has multiple causes. The national appliance stock has a range of efficiencies with they can deliver the same energy service and different people use different amounts of electricity during similar activities. Furthermore, these data span different times of day, days of the week and even times of year, all of which could be separated out in detail once more data have been collected.

In this paper we set out to address the diversity which stems from the conflation of activities which overlap in time. Are some of the values in Fig. 1 distorted by the fact that other activities systematically overlap with them in time and thereby artificially increase the amount of electricity associated with it? For this we translate the E_A values in Fig. 1 into marginal contributions for each activity.

3.2. Marginal demand

A heat map of the marginal contribution $E^*_{A',A}$ for 18106 activity pairs is shown in Fig. 2. Activities are ranked by their original electricity footprint from Fig. 1. Coloured areas describe the change in demand that is observed when A' is reported in addition to A. The most statistically significant pairs are marked *** ($p \leq 0.01$). White areas do not have statistical significance ($p > 0.1$). The total num-

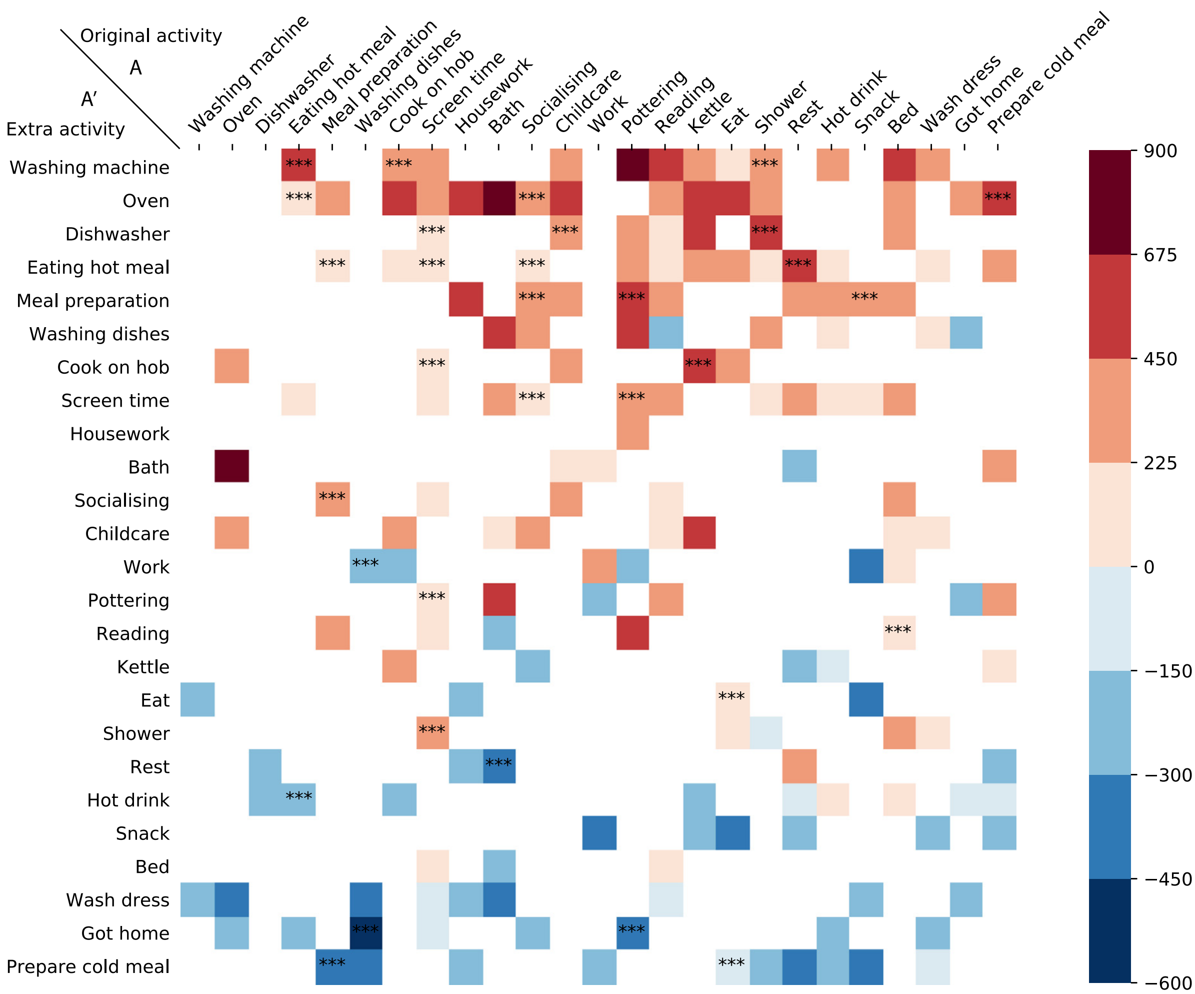

Fig. 2. Marginal contribution of activity A' on A.

ber of occurrences each activity and the number of coincidences within ± 30 minutes is shown in Fig. 6 in the Appendix.

It is worth noting that the matrix is not symmetrical and that directionality matters. Adding activity A to B is not the same as B to A.

This is best illustrated by a pairing of high and low energy footprint: *Washing machine* and *Wash dress*. If *Wash dress* (A') is added to *Washing machine* as the reference activity (A), the marginal contribution is negative (column *Washing machine*, row *Wash dress* in Fig. 2). Household demand tends to be lower when someone reports washing or getting dressed (typically in the morning). Conversely, since demand during *Wash dress* tends to be low on average, the specific times when *Washing machine* is reported in addition, demand is significantly higher (column *Wash dress*, row *Washing machine* dress in Fig. 2). This asymmetry exacerbates the initial energy footprint attribution that *Washing machine* is associated with high demand, whereas *Wash dress* is a low demand activity in Fig. 1. In marginal terms the two activities are now more distinct. Because on some occasions washing machines are used while washing or getting dressed, the footprint attributed to *Wash dress* in Fig. 1 might be an overestimate.

The dynamics and causality which give rise to higher or lower demand are not always self-evident. These can be illustrated with specific examples in Figs. 3 and 4.

The specific load impact of *Hot drink* on some of the most affected activities is shown in Fig. 3. The bars show the electricity footprint for all instances when an activity (A) was reported without a *Hot drink*. The coloured area is the difference reporting of a *Hot drink* made ($E^*_{A'}$). These are the values from row *Hot drink* in Fig. 2.

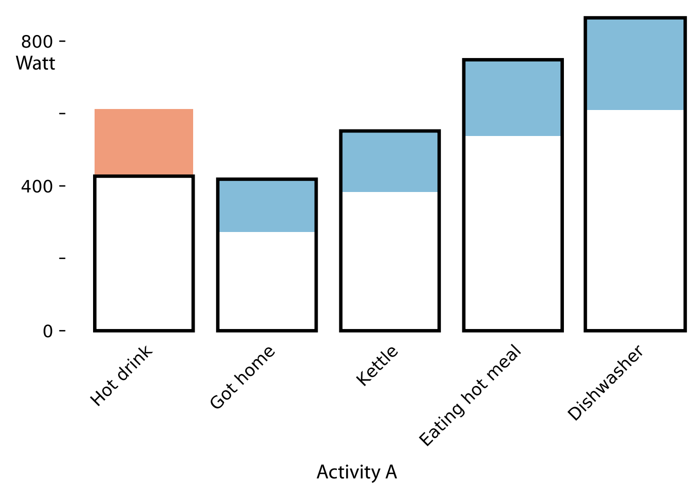

Fig. 3. The effect of a hot drink (A') on selected activities (A).

The marginal demand of a *Hot drink* differs depending on which activity it complements.

Having a hot drink while using the kettle shows a negative marginal demand (column *Kettle*, row *Hot drink* in Fig. 2). One ex-

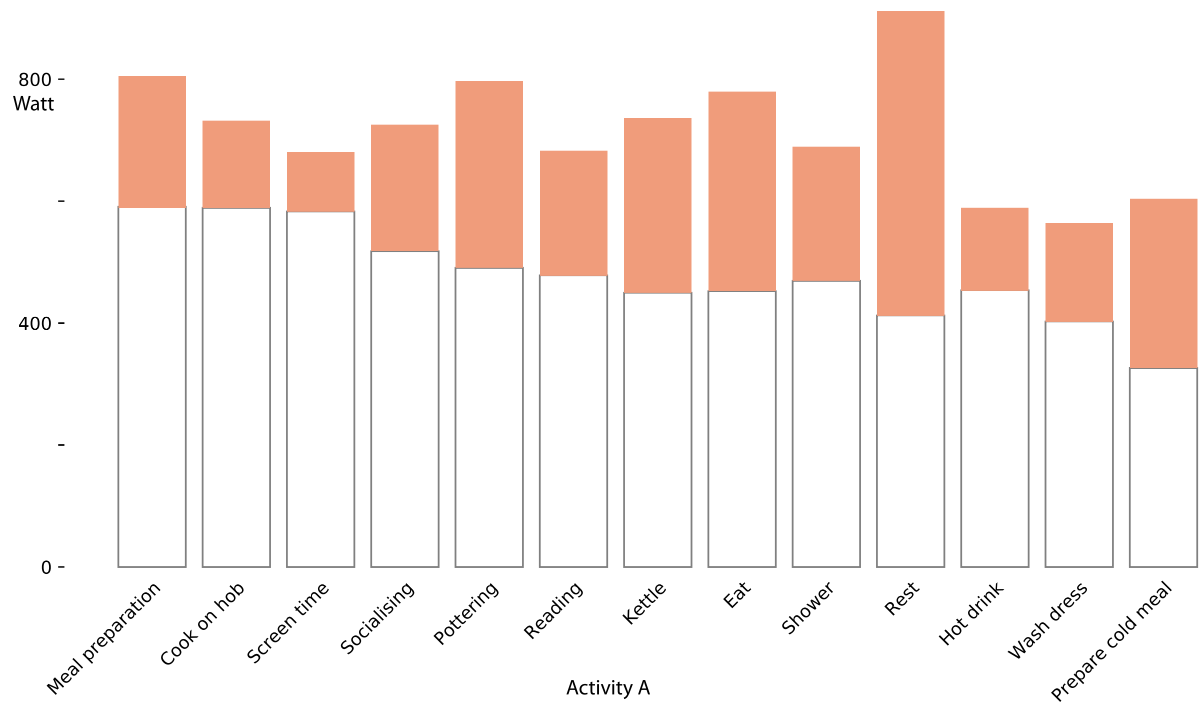

Fig. 4. Increase in demand when *Hot meal* (A') is reported alongside activities (A).

planation is that kettles do not get filled as much for a hot drink than for other uses, such as heating water for cooking. However, it is also possible that the hot drink acts as an indicator for less energy intensive practices at that time. If using a kettle for a hot drink means that the kettle is not used as part of meal preparation, then the overall demand is likely to be lower. Using a *Kettle* in addition to eating a hot meal consequently has a positive marginal demand, whereas a *Kettle* in association with a *Hot drink* results in lower demand (in both directions).

Not surprisingly, if more than one hot drink is reported (*Hot drink* as A and A'), the additional hot drink has a positive marginal demand. This effect is potentially still stronger than the strict energy requirement of preparing the hot drink itself. Boiling a kettle for 3 minutes would raise the average over the one hour period by approximately 100W. The observed marginal demand of 185W suggests that kettles have either been filled unnecessarily or that some additional demand remains unaccounted for.

Active occupancy itself, which is implicit in many activities reported at home, results in the use of lighting and other ancillary activities that go unreported. It can therefore be assumed that part of the marginal values include an element of this demand overhead.

Some other activities in Fig. 3 and the majority of activities in Fig. 2 for *Hot drink* have statistically significant negative effects on demand. Similar explanations as the *Hot meal* dynamic explained above may apply here.

From a social practice perspective, the *Got home* activity may be particularly interesting. The reduction in demand when arriving home and having a hot drink (which is itself a 185 Watt consuming activity), suggests that the *Hot drink* displaces other more electricity-intensive activities and that this effect outweighs the demand for the hot drink itself.

The second activity that has been singled out from Fig. 2 is that of *Eating hot meal*. Fig. 4 shows that *Rest* has the largest impact on *Eating hot meal*. A common occurrence of this pattern is for one household member to report resting while another is active. There are cases where *Rest* is reported before or after *Eating hot meal*. This makes *Eating hot meal* and *Rest* another example of two activities that are distinctly different in their electricity demand, but would have been conflated in the attribution in the previous section. Having a *Rest* when no *Eating hot meal* is reported shows some of the lowest demand, while the addition of *Eating hot meal* has a significant marginal impact of approximately 500 Watt.

Interestingly the higher reference demand for one of the most reported activities, *Screen time*, is less affected by the addition of *Eating hot meal*. At this point one can only speculate whether *Eating hot meal* that is consumed while on a screen is less energy intensive to prepare, potentially because less preparation was involved. *Screen time* is the most ubiquitous activity (see Appendix). *Screen time* without *Eating hot meal* covers many other energy-intensive activities. Therefore the background average of *Screen time* is likely to already be high.

The examples of *Hot drink* and *Eating hot meal* show that the marginal contribution of activities can be sensitive to their activity context. Nonetheless, some general trends can be observed. In a second step of aggregation Fig. 5 shows the general effect of activities (A') across all statistically significant ($p \leq 0.1$) pairings with activities (A) as per Eq. (6), which produces a single value $E^*_{A'}$ per row in Fig. 2.

The marginal activities demand figures result in overall lower values compared to Fig. 1, and indeed some negative ones. Each value is now more closely aligned with the activity itself and less so with the general (background) demand of other activities at the time. Especially for the appliance related activities, such as *Washing machine, Oven* or *Dishwasher* these numbers should not be confused with appliance ratings. 400 Watt for an oven is not the power of the oven, but merely the effect the oven had on demand for the 30 minutes before or after (more likely after) a participant reported another activity. The oven may only have been in use for 15 minutes or for a considerable time beyond the 30 minutes.

Even seemingly energy unrelated activities, such as socialising or resting, still lead to higher demand. *Reading* on the other hand, which had an initial demand attribution of 460 Watt could be identified as a low demand activity in marginal terms.

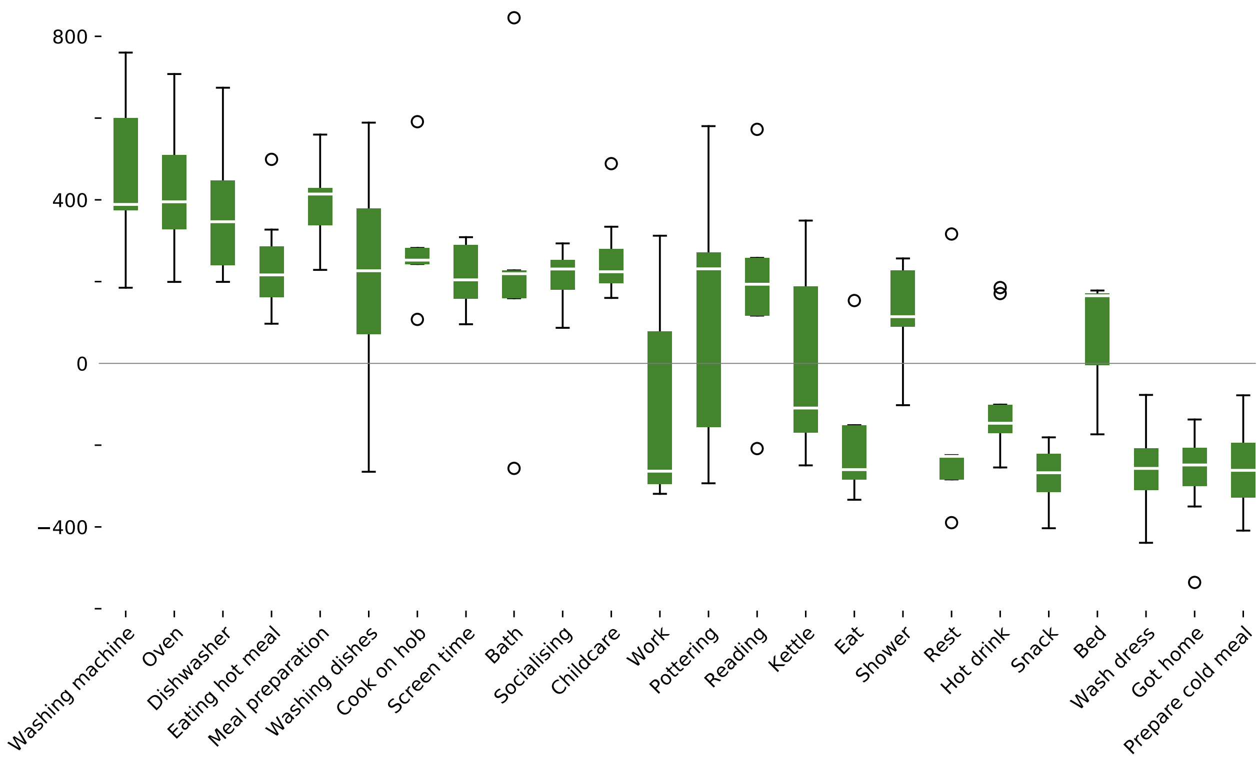

Fig. 5. Aggregate marginal contribution of activities on demand. Whiskers mark the full range, circles are outliers (>2.5 times the interquartile range).

The trend that hot meal related activities are among the highest drivers of demand, whereas *Preparing cold meal* has the strongest negative impact on demand confirms the initial trend in Fig. 1.

The distribution of marginal contributions differs significantly between different activities in Fig. 5. This is a compound effect of two distributions. Firstly, different activities are paired with different numbers of other activities (see Fig. 2 for significance of joint activities and Fig. 6 for absolute numbers). Secondly, each of these other activities have themselves different distributions.

Better defined activities with tight distributions tend to coincide with a greater number of activities with high statistical significance in Fig. 2 (marked ***) and common direction. *Eating hot meal* is paired with 13 other activities, all showing an increase in demand and four with high significance ($p \leq 0.01$). The resulting distribution is therefore narrow. Kettles, as an example of a wide distribution, are paired with two activities for which they increase load (*Cook on hob* and *Prepare cold meal*) and three for which they reduce it (*Socialising, Rest, Hot drink*).

4. Discussion

This analysis has shown that electricity use is more strongly related to the activity patterns than initially observed by [17]. The improved grouping of activities brings out clearer distinction between activities. The inclusion of combinatorial effects further improves the explanatory power of activity data. Marginal activity contributions enhance the precision with which activities can be linked to electricity demand and also allows for activities to be attributed to a reduction in demand.

The data available for this analysis is still limited. With a larger sample it may be possible to refine the approach and deploy more sophisticated regression and machine learning techniques. Furthermore, it may become possible to discriminate the data more in terms of demographics, time of day or time of year. By dividing the sample into different age groups it would be possible to identify demographics shifts in demand for similar activities. Many other segmentations are also possible and can be explored with sufficiently large and representative samples.

The cost of data collection has been significantly reduced in recent years, such that further data collection should be encouraged. Artificial Intelligence approaches could learn from activity patterns, such that widely available smart meter profiles can be used for unintrusive information gathering. Ethical implications and potential for misuse of such approaches are in urgent need of investigation.

The focus on household activities offers new perspectives on electricity demand and the role of social practices in shaping it. One of the most commonly reported activities, *Hot drink*, has been shown to lead to a reduction in demand at the time of reporting, despite the fact that the preparation of a hot drink itself requires energy.

It may therefore be possible to lower demand by encouraging activities that are themselves electricity demanding, but have a negative marginal demand.

This effect, which may or may not be causal, raises interesting questions over the role of activities in displacing other (more energy intensive) activities. This approach could lead to new, less punitive or restrictive approaches to load reduction or shifting. Cold meals are another obvious example. The relationship between meals, their timing and social dynamics (whether consumed alone or in company) could hold the key to innovative approaches that could go beyond energy and also benefit health and well-being.

Additional qualitative research may help to further understand some of the dynamics between activities, where seemingly unrelated activity combinations (dishwashing alongside bathing or pottering) result in significant increases in demand. Here it can be just as important to understand which activities can lead to other activities *not* to be performed.

5. Conclusions

This paper presents a novel method for collecting and analysing household activity and electricity use data. Data post-processing approaches include grouping and de-minning, which result in meaningful attributions between activity records and their associated electricity demand.

The direct attribution of activities to household electricity demand shows clear differences between key groups of activities. Times of hot meals emerge as significant high load periods, while cold meals are among the lowest. The method for attributing these footprints includes any activities that were performed at the time. Using an oven before, or a dishwasher after a hot meal can count as part of the energy demand of the hot meal itself.

Distinctions between activities can therefore be drawn more clearly after the introduction of marginal demands. This approach allows to disaggregate activities that coincide in time. Marginal activity demand provides a more specific contribution of an activity to electricity demand.

Hot meals stand out even more clearly as one of the dominant activities to explain high electricity demand, with marginal demand contributions of over 230 Watt during that hour. Cold meals could be identified as one of the lowest energy demanding activities with a marginal demand of -250 Watt.

One of the most commonly reported activities, *Hot drink*, is itself an energy demanding activity. However, this analysis suggests that at times when it is reported net demand is in fact reduced. In some cases the *Hot drink* displaces other, more energy intensive activities. Further analysis and studies with deliberate interventions may be able to establish the underlying dynamics and causal effects more clearly.

The concept of marginal activity demands may enable the development of new approaches to reduce or shift demand. The relationships between electricity use and activities, but also between activities themselves, raises many questions for which a larger data sample would be required. We further encourage to follow some to these relationship up with qualitative research methods to complement this quantitative approach taken here.

Declaration of Competing Interest

None.

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Appendix

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Extra activity (A′) \ Original activity (A)	Oven (231)	Washing machine (141)	Eating hot meal (531)	Meal preparation (199)	Cook on hob (271)	Washing dishes (164)	Screen time (1863)	Other appliance (120)	Housework (206)	Bath (113)	Socialising (283)	Childcare (290)	Work (136)	Kettle (155)	Pottering (261)	Reading (228)	Eat (434)	Snack (143)	Shower (349)	Hot drink (544)	Rest (157)	Bed (542)	Wash dress (538)	Got home (142)	Prepare cold meal (126)
Oven	39	13	109	26	31	12	168	17	10	4	31	28	17	14	16	19	29	5	12	24	12	7	12	26	5
Washing machine	12	20	24	9	14	15	88	5	21	8	10	13	6	5	11	13	19	3	20	27	0	12	33	5	4
Eating hot meal	63	15	290	89	106	62	345	16	27	13	66	42	15	35	31	33	54	11	25	61	21	15	44	12	11
Meal preparation	21	9	94	59	26	32	165	7	17	7	21	16	4	18	20	14	62	10	25	41	13	11	46	2	15
Cook on hob	31	12	171	35	87	19	183	10	14	2	31	22	8	28	17	10	20	13	16	25	11	10	25	12	8
Washing dishes	9	13	67	34	17	39	132	11	20	14	22	23	7	14	19	16	46	6	17	41	8	19	36	3	19
Screen time	99	64	272	111	133	90	1066	63	97	41	139	114	61	83	100	109	160	88	113	263	84	137	195	61	46
Other appliance	16	5	22	10	13	8	98	32	5	0	8	7	3	12	8	9	25	13	17	25	5	21	45	9	4
Housework	9	18	32	16	13	17	132	6	43	5	20	25	9	12	25	12	39	5	25	35	11	18	42	5	9
Bath	5	6	9	4	2	8	50	0	4	50	7	58	4	2	5	6	14	2	6	12	5	10	13	4	1
Socialising	23	12	67	18	24	19	166	10	18	11	151	26	11	7	25	28	12	13	15	31	18	33	28	18	4
Childcare	26	9	48	19	23	16	146	7	23	43	28	107	11	6	22	29	31	13	21	23	9	37	34	20	8
Work	16	5	17	4	10	8	101	3	7	4	16	11	16	8	7	8	15	8	6	30	2	12	12	12	3
Kettle	13	5	45	23	34	15	115	10	12	2	4	7	8	41	16	14	30	11	20	58	9	14	38	4	12
Pottering	13	10	46	21	14	22	132	7	18	9	27	22	8	18	79	32	57	17	34	41	10	41	73	9	22
Reading	17	13	33	21	12	17	150	8	11	7	30	23	8	15	28	76	32	12	25	49	29	76	46	7	7
Eat	21	14	54	51	15	34	188	22	31	15	19	30	13	21	41	22	173	3	93	89	19	28	160	13	64
Snack	3	4	12	11	14	7	117	12	6	6	19	16	6	11	20	13	5	37	7	39	12	13	21	15	1
Shower	14	17	37	19	13	19	142	20	19	10	18	25	6	16	40	24	115	5	102	77	9	56	218	4	31
Hot drink	29	20	56	40	24	33	341	24	33	14	32	25	29	45	41	49	94	35	71	148	25	54	117	18	33
Rest	9	0	21	9	18	6	118	4	15	7	29	9	2	13	12	27	16	13	10	27	29	22	35	9	6
Bed	5	10	10	10	9	11	134	14	12	10	33	32	5	15	32	55	38	9	58	45	16	282	137	7	11
Wash dress	8	16	42	24	17	26	187	27	28	12	26	39	7	24	51	46	140	16	164	100	27	122	311	5	45
Got home	33	5	23	4	11	3	83	7	9	3	17	21	6	6	7	8	14	18	5	19	11	11	7	29	4
Prepare cold meal	5	4	15	17	7	19	50	7	7	0	5	7	2	9	19	11	85	1	30	34	9	8	77	4	39

Fig. 6. Number of coinciding activities within ± 30 minutes. Total number reported in brackets.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.enbuild.2019.109498.

References

[1] UK Government (2019). UK becomes first major economy to pass net zero emissions law [online] [cited 15 July 2019].
[2] National Infrastructure Commission (2016). Smart power, national infrastructure commission report, National Infrastructure Commission.
[3] A. Grubler, C. Wilson, N. Bento, B. Boza-Kiss, V. Krey, D.L. McCollum, N.D. Rao, K. Riahi, J. Rogelj, S. De Stercke, et al., A low energy demand scenario for meeting the 1.5 c target and sustainable development goals without negative emission technologies, Nat. Energy 3 (6) (2018) 515.
[4] N. Eyre, S.J. Darby, P. Grünewald, E. McKenna, R. Ford, Reaching a 1.5C target: Socio-technical challenges for a rapid transition to low carbon electricity systems, The royal society. philosophical transactions a., 2017.
[5] Eyre, N., & Killip, G. (2019). Shifting the Focus: Energy Demand in a Net-Zero Carbon UK. Tech. rep. Centre for Research into Energy Demand Solutions. Oxford, UK. 978-1-913299-00-2.
[6] F. Bowden, D. Lockton, C. Brass, R. Gheerawo, Drawing Energy: Exploring the Aesthetics of the Invisible, IAEA congress 2014: Congress of the international association of empirical aesthetics, 2014.
[7] J. Burgess, M. Nye, Re-materialising Energy use Through Transparent Monitoring Systems, Energy Policy 36 (12) (2008) 4454–4459.
[8] CER (2011). Electricity Smart Metering Customer Behaviour Trials Findings Report. Information paper cer11080a The Commission for Energy Regulation.
[9] Schofield, J., Carmichael, R., Tindemans, S., Woolf, M., Bilton, M., & Strbac, G. (2014). Residential Consumer Responsiveness to Time-Varying Pricing. Report a3 for the "low carbon london" lcnf project Imperial College London.
[10] Frontier Economics (2015). Insight Report: Enhanced Domestic Monitoring. Clnr-l094 Customer-Led Network Revolution.
[11] J.-P. Zimmermann, M. Evans, J. Griggs, N. King, L. Harding, P. Roberts, C. Evans, Household electricity survey — a study of domestic electrical product usage, 2012 Report r66141. Intertek [Online] Available from: http://randd.defra.gov.uk.
[12] J. Palmer, N. Terry, T. Kane, S. Firth, M.H.P. Pope, J. Young, D. Knight, D. Godoy-Shimizu, Electrical appliances at home: tuning in to energy saving, further analysis of the household electricity use survey, Cambridge architechural research limited, element energy, loughborough university, 2013.
[13] L. Stankovic, V. Stankovic, J. Liao, C. Wilson, Measuring the energy intensity of domestic activities from smart meter data, Appl. Energy 183 (2016) 1565–1580.
[14] M. Weiss, A. Helfenstein, F. Mattern, T. Staake, Leveraging smart meter data to recognize home appliances, in: 2012 IEEE international conference on pervasive computing and communications, IEEE, 2012, pp. 190–197.
[15] Bulkeley, H., Bell, S., Lyon, S., & Powells, G. (2013). Social science interim report 2. Tech. rep. Customer-Led Network Revolution.
[16] Y. Strengers, Peak electricity demand and social practice theories: Reframing the role of change agents in the energy sector, Energy Policy 44 (2012) 226–234, doi:10.1016/j.enpol.2012.01.046.
[17] P. Grunewald, M. Diakonova, The electricity footprint of household activities - implications for demand models, Energy Build. 174 (2018) 635–641, doi:10.1016/j.enbuild.2018.06.034.
[18] Richardson, I., & Thomson, M. (2007). CREST domestic electricity demand model. URL https://dspace.lboro.ac.uk/dspace-jspui/handle/2134/5786.
[19] S.D. Lauretis, F. Ghersi, 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, doi:10.1016/j.apenergy.2017.08.180.
[20] A. Sekar, E. Williams, R. Chen, Changes in time use and their effect on energy consumption in the united states, Joule (2018) 2542–4785, doi:10.1016/j.joule.2018.01.003.
[21] B. Anderson, J. Torriti, Explaining shifts in uk electricity demand using time use data from 1974 to 2014, Energy Policy 123 (2018) 544–557, doi:10.1016/j.enpol.2018.09.025.
[22] J.L. Ramirez-Mendiola, P. Grünewald, N. Eyre, Linking intra-day variations in residential electricity demand loads to consumers' activities: What's missing? Energy Build. 161 (2018) 63–71, doi:10.1016/j.enbuild.2017.12.012.
[23] 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 Effic. (2017) 1–15, doi:10.1007/s12053-017-9525-4.
[24] eurostat (2014). Harmonised european time use surveys, 2008 guidelines, Office for Official Publications of the European Communities.
[25] METER, UK household electricity and activity survey, 2016-2019: Secure access, Data repository, UK data service, 2019, doi:10.5255/UKDA-SN-8475-1.
[26] ONS (2018). Family resources survey, 2015/16, online, Office for National Statistics. URL https://www.gov.uk/government/statistics/family-resources-survey-financial-year-201516.
[27] ONS (2015). Population estimates for UK, England and Wales, Scotland and Northern Ireland: mid-2015, online, Office for National Statistics. URL https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/bulletins/annualmidyearpopulationestimates/mid2015.
[28] ONS (2017a). Families and households in the UK: 2016, online, Office for National Statistics. URL https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/families/bulletins/familiesandhouseholds/2016.
[29] ONS (2017b). Percentage of households with durable goods, UK, table a45, Office for National Statistics. URL https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/expenditure/datasets/percentageofhouseholdswithdurablegoodsuktablea45.
[30] UKERC-EDC (2017). Domestic washing machine - appliance ownership levels. Data repository UK Energy Research Centre Energy Data Centre (UKERC-EDC). URL http://data.ukedc.rl.ac.uk/simplebrowse/edc/efficiency/residential/Appliances/Domestic_Washing_Machines.
[31] P. Grünewald, M. Diakonova, D. Zilli, J. Bernard, A. Matousek, What we do matters – a time-use app to capture energy relevant activities, in: eceee 2017 summer study proceedings, 2017, pp. 2085–2093.
[32] Grünewald, P. (2017). Meter app. Source code repository GitHub. URL https://github.com/PhilGrunewald/MeterApp.
[33] J. Gershuny, O. Sullivan, Time use, gender, and public policy regimes, Soci. Politics: Int. Stud. Gender, State Soc. 10 (2) (2003) 205–228.
[34] D.S. Hamermesh, G.A. Pfann, Time-use data in economics, Eur. Econ. Rev. 49 (1) (2005) 1–7, doi:10.1016/j.euroecorev.2004.03.011.
[35] B. Anderson, Laundry, energy and time: Insights from 20 years of time-use diary data in the United Kingdom, Energy Res. Social Science 22 (Supplement C) (2016) 125–136, doi:10.1016/j.erss.2016.09.004.
[36] K. Ellegård, Time Geography in the Global Context: An Anthology, Routledge, 2018.
[37] A. Satre-Meloy, M. Diakonova, P. Grünewald, Daily life and demand: an analysis of intra-day variations in residential electricity consumption with time-use data, Energy efficiency, Apr 2019, doi:10.1007/s12053-019-09791-1.