Diversity behind the meter - machine learning from household activities

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Abstract

Consumers use energy without knowing or wanting to know much about how energy is being delivered to them. For consumers to genuinely move to the 'heart of the energy system', the reverse disconnect may also need to be addressed: generators and suppliers of energy know surprisingly little about what their customers need this energy for. This two-way gap in knowledge is becoming more problematic in low carbon systems, where the timing and flexibility of demand is critical.

We present data from the first study of its kind exploring at scale what happens behind the meter, not just in terms of appliance use, but the actual activities that give rise to times of high or low consumption. A better understanding of these dynamics is important to develop more consumer focussed business models that reflect the significant diversity in usage patterns and their flexibility.

Our data collection method is a combination of high resolution household electricity recordings, with simultaneous app based activity reporting [www.energy-use.org]. The parallel collection of data allows new analytical tools to shine a light on the relationship between activities, socio-demographics, appliance ownership and the timing of electricity use. The finding presented here are based on a sample of over 8000 activity records. The collection of data started in 2016 and is ongoing.

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Machine learning and advanced regression techniques have been applied to establish often complex relationships. Our paper gives specific examples of some activity patterns that relate to high or low usage. More complex patterns of activity sequences are also presented. The approach allows new and refined clusters of consumers to be identified, including groups that are more or less likely to be able to engage in load shifting.

We conclude that the diversity of demand is an opportunity for better targeted business models to achieve greater demand response engagement. Without a detailed understanding of what energy is used for, policies are likely to be designed for ill defined 'typical' users, thereby missing commercial opportunities while at the same time failing many customers who could be engaged better. This understanding will help to ensure that consumers can indeed be at the heart of the energy system.

1 Intoduction - the electricity meter as a barrier

Whole systems energy thinking is inhibited by a physical and cognitive barrier: the electricity meter. Upstream of the meter, systems research often considers the meter as the system boundary easily characterised as a load profile, whereas behind the meter energy users pay little attention to the goings on that enable their uninhibited use of electricity.

The electricity meter facilitates this disconnect further by creating some false simplifications in the transaction between user side and the provision side of the system. In the UK and many other countries electricity meters are used to charge by the kWh at a flat rate. Especially with increasing shares of renewable sources of energy neither the kWh nor the flat rate are appropriate or cost reflective measures. The cost of provision is more closely related to capacity (kW) and flexibility or ramping ability (kW/h) and thus varies greatly over time. This has led to a call for a fundamental reversal of roles between these two sides of the meter. No longer is the supply side supposed to deliver what ever the demand side 'demands', but demand itself is supposed to become flexible to suit the availability of supply.

The expectation is that energy users should show a greater interest in matters of 'the system' (National Infrastructure Commission 2016, HM Government (2017)). While parts of the population are indeed keen to engage, for many others the state of the system is low on their list of priorities. Even among the most engaged, the interests of the wider system are not always the main motivation. Many adopters of home battery systems use them to become more grid independent, thereby potentially increasing balancing challenges with their remaining load.

For better whole system solutions this paper argues that a detailed understanding of the value of electricity to users can provide an important counter part to work concerned with the cost of electricity.

Just as the cost of electricity varies over time, so does the value to energy users. Depending on the energy service, very different willingness to pay can be observed. Festival goes happily pay £4 to charge their mobile phones[2], which equates to £800,000 per MWh, while heating systems delivering more heat than desired due to inappropriate controls can constitute negative energy value.

What we do with electricity therefore matters. A deeper understanding of the goings on behind the meter could help to understand how the balance between the cost of provision on one side and the value of its use on the other can be better balanced.

Time-use data has become widespread in attempts to better understand and model energy use (Richardson and Thomson 2007, Sekar, Williams, and Chen (2018)), the temporality of demand (Anderson 2016) and even intrinsic flexibility of demand (Torriti et al. 2015). However, time use data is collected without energy recordings and these studies have to make difficult inferences on how activities may relate to consumption at aggregate level (Ramírez-Mendiola, Grünewald, and Eyre 2018).

Time-use tariffs are an attempt to reveal the price elasticity of electricity use. However, they cannot reveal non-monetary constraints that may be inhibiting more flexible use of electricity. These could include social constraints like working and schooling hours. Social norms of when to have hot meals can also play an important role in shaping electricity use. Social synchronisation, such as described by Walker (2014) can be another powerful force resisting changes in electricity use, which are difficult to reveal with time use pricing experiments.

In this paper we present findings from a study on the relationship between household activities and electricity use. We present methods that allow to generalise patters in activity data.

Our data collection method is a combination of high resolution household electricity recordings, with simultaneous app based activity reporting [www.energy-use.org]. The parallel collection of data allows new analytical tools to shine a light on the relationship between activities, socio-demographics, appliance ownership and the timing of electricity use. The finding presented here are based on a sample of over 8000 activity records. The collection of data started in 2016 and is ongoing.

For further detail about the study and its methodology, see Grünewald et al. (2017) and Grunewald and Diakonova (2018).

[2]This service is offered commercially and transacted many times by satisfied customers

2 Patterns of activity

Appliances have well defined load characteristics. A kettle, for instance is shown in Figure 1a. The distinct signature of this appliance was used by Grunewald and Diakonova (2018) to calibrate the accuracy of activity reporting. In 80% of cases the kettle signature can be found within 10 minutes of the reported activity.

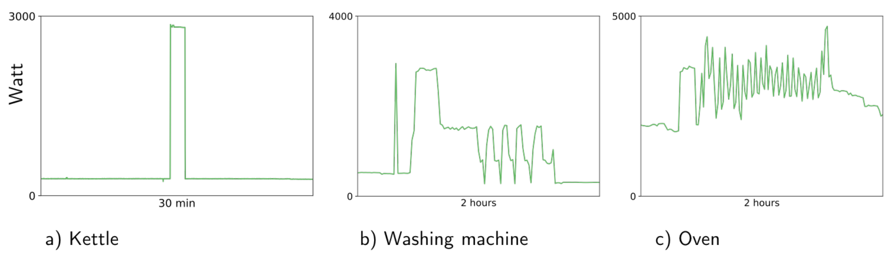

Figure 1: Appliance signatures

Other appliances, such as ovens and washing machines can also be attributed to reporting events (Figure 1 b-c). The novelty of the activity record is that supposedly non-energy related activities can also be attributed a load shape. Figure 2a shows a typical profile of electricity use at the time when 'going to bed' was reported as an activity. The example in Figure 2a has been picked as a representative profile. In practice the electricity use during this activity is highly diverse. With 986 reported activities relating to 'bed' or 'sleep' is it possible to generalise on the load trend during this activity.

Figure 2b shows the generic trend in the hour surrounding 'going to bed'. Despite significant diversity, which should be expected especially in multi-occupant households where bed time may differ between different household members, a drop in electricity use of over 25% can be observed for this event.

A similarly clear trend exists for arriving home. Again, the activity itself does not involve any energy consumption *per se*, but it can act as a predictor for changes to the use profile. Figure 3a shows a selected example of an individual home, whereas Figure 3b shows the general trend for a sample of 183 events.

These two examples are special cases, where activities lead to a clear trend. The vast majority of activities tend to be overlapping with each other too much to identify individual trends clearly. New techniques are therefore required and we present some promising activity sequencing approaches here.

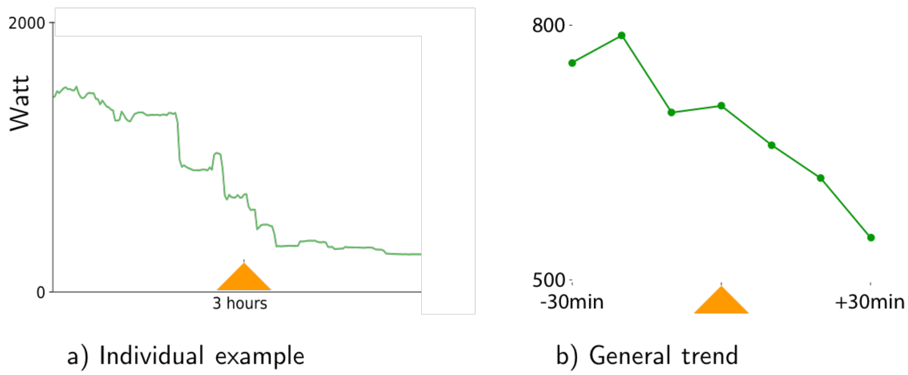

Figure 2: Electricity signature of going to bed. The orange marker indicates the time of reporting the activity.

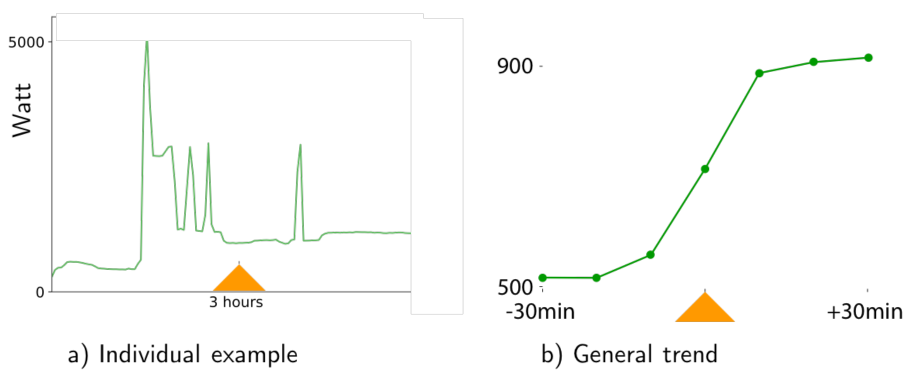

Figure 3: Electricity signature of getting home. The orange marker indicates the time of reporting the activity.

3 Activity sequences

To strengthen the predictive power of activities for electricity use it is possible to consider clusters of activities. Figure 4 illustrates an ActiviTree for the activity of eating a hot meal. Below the activity itself are any activities that were reported prior to it, in the preceding 10 minutes, 30 minutes or 60 minutes. Conversely, activities reported after eating a hot meal are arranged above. Activities with less than 10 mentions have been grouped together in the Others category.

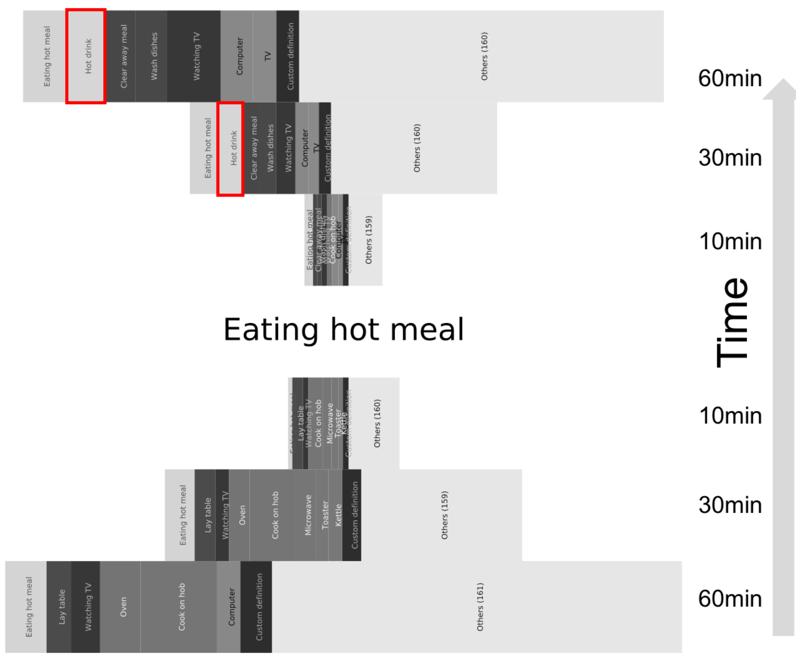

Figure 4: ActiviTree representation of activity sequences before and after having a hot meal.

Many of the pairings in Figure 4 to have practical relationships, such as use of an oven or a hob. One of the most common successors to a hot meal is a hot drink. This pairing thus allows to dive one level deeper and explore how the combination of two activities narrows the scope for other activities happening before, after, or indeed between this pair of activities.

Figure 5 shows the PairTree of hot meal followed by hot drink and the distribution of activities in the surrounding hour.

An example of the predictive power of this approach is illustrated in Figure 6. Travelling to work can be predicted with 80% probability if Shower and Getting Dressed have been reported as a pair. This is not to say that 20% of people do

Figure 5: PairTree representation of two activities with preceding, intervening and subsequent activities.

not get dressed between a shower and travelling to work.

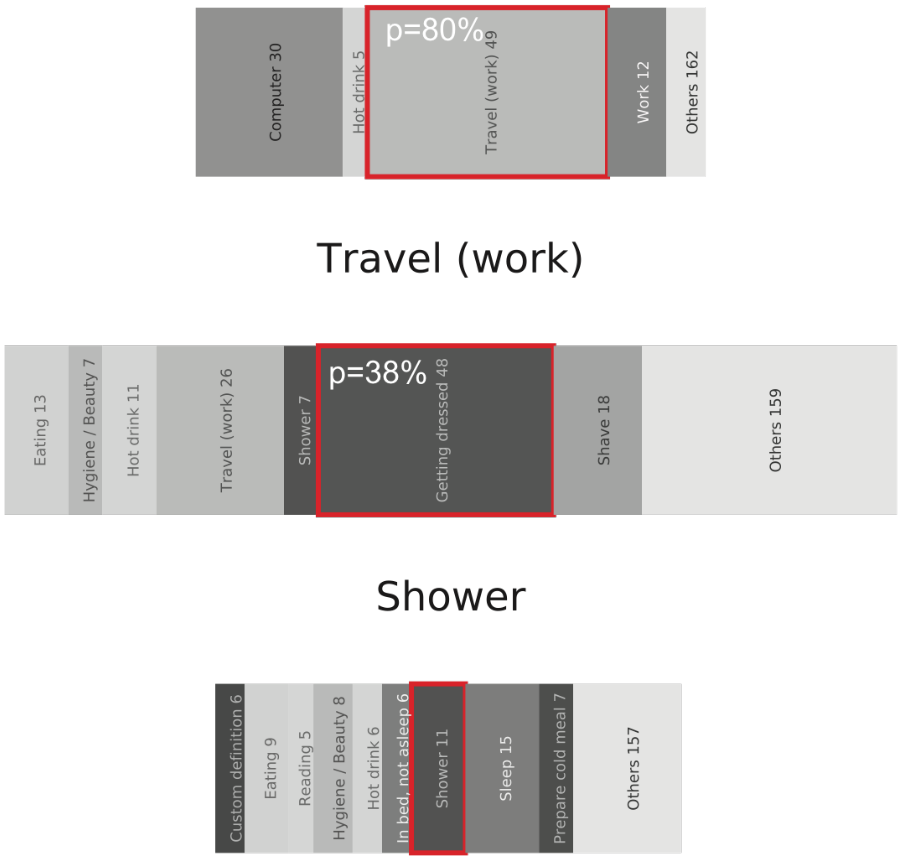

Figure 6: Improved predictability of a third activity following an activity pair being reported.

4 Discussion

Machine learning approaches clustering load profiles and combinations of activities may be able to identify particular socio-demographic groups with particular load shifting potential. In the first instance it may become increasingly possible to define characteristics that lead to high peak time electricity use. Such households could be targeted with policy interventions or business models that suit their particular requirements.

For such algorithms to produce reliable results more data will need to be collected. Smart meters promise to enhance electricity data collection by reducing the cost of monitoring. Integration of the activity collection process into automated smart appliances and personal smart phone usage observations could ease the reporting burden on participants, provided that privacy concerns can be avoided. Smart phones alone hold significant information about app usage and location data that allow this type of analysis to be performed without much additional user input.

The applications of these data are wide ranging. Load prediction can help storage and other system operators better schedule their assets. New business models to deliver demand side responses can target the most promising user groups and refine the incentive structures to meet their particular needs and value expectations. A better understanding of the likelihood of flexibility being forthcoming at different times and from different demographics can further inform the need to invest in other sources of flexibility.

Alongside direct interventions, broader non-energy policies may also benefit from these data. The role of working or schooling hours on the shape of load profiles may open long term opportunities to re-shape load profiles to better suit system needs.

5 Conclusion

We have shown that reported activities can help to predict load profiles and these can be used to improve the modelling accuracy of household demand. For some activities and many appliances it is possible to make direct load attributions. The diversity of household activities and potential overlaps within multi-occupant households calls for more sophisticated approaches. We have presented an activity sequencing approach that could go some way towards better predictability and understanding of household load profiles.

The continued collection of data will help to test these approaches for their statistical validity and may also yield insights into shifting trends in usage patterns over time. In particular the adoption of electric vehicles, heating and increased use of digital services can be documented using this approach.

Further work will contrast these profiles and activity sequences with responses to interventions, such as price signals or requests to avoid electricity use. With a robust baseline it will be possible to identify flexibility and inhibitors to flexibility in household electricity consumption.

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