Understanding domestic appliance use through their linkages to common activities

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Objectives of study

Understanding the linkages between appliance use and common activities in the house by integrating **quantitative smart home data** with **qualitative household ethnography** to identify activities at home

Develop, test, and validate a multi-step methodology for making robust activity-based inferences in households

Demonstrate how smart energy meter data can be used to feed back information to households on the time profile of everyday activities in the home and their energy-using consequences
Meaningful feedback

Feedback is important “in making energy more visible and more amenable to understanding and control” [1].

Moving away from ‘energy-centric’ approach in which information feedback directly concerns energy consumption.

To an ‘activity-centric’ approach, where the emphasis shifts from energy use to households’ lived experience, i.e., routines, habits and activities that constitute the majority of life at home.

Task: Infer a comprehensive set of activities to describe household life and energy use.

**DAILY ROUTINES:**

**INTERACTING:** communicating, socialising

**LEISURE & ICTs:** watching TV, listening to radio/music, gaming, computing

**OTHER ACTIVITIES:** hobbies, caring, working, other
Smart electricity meters tell us about real-time household electricity use, but they don’t tell us which appliances were running, nor **what to do about it**.

Energy disaggregation tells us **when and how long** an appliance was used, but nothing about **why** it was used.

Using disaggregated power readings, *develop an autonomous activity recognition system* and estimate power consumption and time use per activity.

1. The routines and scheduling of domestic life explain why and when electricity is used.
2. To be meaningful and salient, energy feedback needs to reflect households’ lived experience.
Methodology, step-by-step

1. Define activities
   comprehensive set of activities meaningful to households

2. Build activity ontology
   map technology <-> activity relationships (noting uncertainties)

3. Collect real-time data
   collect & process smart meter data from homes

4. Disaggregate data
   process data using NALM algorithms

5. Infer activities
   process data using activity ontology and inference algorithms
Building an Activity Ontology

- Household interviews & video + Ethnography of practices
- From house survey, make inferences from location information: activity <-> room mapping
- Activity time diaries
- Inferences from electrical data: disaggregation result
Examples of a part of an ontology

<table>
<thead>
<tr>
<th>Type</th>
<th>Appliance / Technology</th>
<th>cooking</th>
<th>eating</th>
<th>washing</th>
<th>laundering</th>
<th>cleaning</th>
<th>sleeping</th>
<th>tv</th>
<th>radio</th>
<th>games</th>
<th>computing</th>
</tr>
</thead>
<tbody>
<tr>
<td>electricity</td>
<td>kettle</td>
<td>x</td>
<td>o</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>electricity</td>
<td>toaster</td>
<td>x</td>
<td>o</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>electricity</td>
<td>microwave</td>
<td>x</td>
<td>o</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>electricity</td>
<td>washing machine</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>electricity</td>
<td>vacuum cleaner</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>electricity</td>
<td>food processor</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>x</td>
<td>~</td>
<td>x</td>
</tr>
<tr>
<td>electricity</td>
<td>PC</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>x</td>
</tr>
<tr>
<td>electricity</td>
<td>laptop</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>~</td>
<td>x</td>
</tr>
</tbody>
</table>

+ additional information on:
- location
- typical usage patterns

**x** = marker technology

**~** = auxiliary technology

**o** = associated activity
Energy Disaggregation

- Non-Intrusive Appliance Load Monitoring (NALM) used to disaggregate energy consumption from a single energy monitor with no alterations to the household fabric/infrastructure
- *Virtual sensors* created, capturing energy consumption (power load) at appliance level with a quantifiable level of uncertainty
- Very active research topic
  - Currently, only few commercial solutions that operate well only at high sampling rates ~kHz, ~MHz
  - Addressing complexity and modest performance of popular Hidden Markov Model (HMM)-based solutions at low sampling rates (>1Hz)
Disaggregation Results Example

- After disaggregation, the following appliance usage information is obtained:
  - start time,
  - duration,
  - mean active power
  - total consumption

<table>
<thead>
<tr>
<th>Date</th>
<th>ST</th>
<th>ET</th>
<th>A</th>
<th>EP [W]</th>
<th>D [sec]</th>
<th>CP [kWh]</th>
</tr>
</thead>
<tbody>
<tr>
<td>08/11/2013</td>
<td>12:31</td>
<td>14:15</td>
<td>Fridge</td>
<td>69</td>
<td>6227</td>
<td>119.70</td>
</tr>
<tr>
<td>08/11/2013</td>
<td>13:50</td>
<td>14:14</td>
<td>Boiler</td>
<td>67</td>
<td>1452</td>
<td>27.02</td>
</tr>
<tr>
<td>08/11/2013</td>
<td>14:15</td>
<td>15:58</td>
<td>Fridge</td>
<td>7</td>
<td>6148</td>
<td>12.22</td>
</tr>
<tr>
<td>08/11/2013</td>
<td>14:37</td>
<td>14:39</td>
<td>Toaster</td>
<td>998</td>
<td>133</td>
<td>36.88</td>
</tr>
<tr>
<td>08/11/2013</td>
<td>14:39</td>
<td>14:40</td>
<td>Fridge door</td>
<td>15</td>
<td>35</td>
<td>0.15</td>
</tr>
<tr>
<td>08/11/2013</td>
<td>14:41</td>
<td>14:41</td>
<td>Fridge door</td>
<td>15</td>
<td>12</td>
<td>0.05</td>
</tr>
<tr>
<td>08/11/2013</td>
<td>15:20</td>
<td>15:22</td>
<td>Kettle</td>
<td>2729</td>
<td>144</td>
<td>109.17</td>
</tr>
<tr>
<td>08/11/2013</td>
<td>17:33</td>
<td>18:46</td>
<td>TV</td>
<td>161</td>
<td>4417</td>
<td>197.52</td>
</tr>
</tbody>
</table>

ST=start time, ET=end time, A=appliance, EP=effective power, D=duration, CP=consumed power

**Results:** Activity-inference methodology applied to **6 homes** for **1 month** (October 2014).

<table>
<thead>
<tr>
<th>House</th>
<th>Size &amp; Composition</th>
</tr>
</thead>
<tbody>
<tr>
<td>House 4</td>
<td>2 retired adults</td>
</tr>
<tr>
<td>House 8</td>
<td>2 retired adults</td>
</tr>
<tr>
<td>House 2</td>
<td>2 adults + 2 pre-school children</td>
</tr>
<tr>
<td>House 10</td>
<td>2 adults + 2 pre-school children</td>
</tr>
<tr>
<td>House 5</td>
<td>2 adults + 2 school children</td>
</tr>
<tr>
<td>House 19</td>
<td>2 adults + 2 school children</td>
</tr>
</tbody>
</table>
Results: 48-82% of electrical appliances were detected. Homes contain 32 to 55 appliances.

- Low power appliances (<20W) such as electric toothbrush, printer, router, DAB radio get ‘lost’ in the aggregate data and account for the percentage of appliances that cannot be detected.
Results: 7-8 activities were inferable in each home (remainder were not inferable or not occurring in that home).

- Each activity can be inferred with different levels of uncertainty:
  - 0 = not inferable, 1 = inferable with uncertainty, 2 = partially inferable, 3 = inferable with high certainty
**Results:** Time-use and electricity consumption of cooking across all households

<table>
<thead>
<tr>
<th>House</th>
<th>House 2</th>
<th>House 4</th>
<th>House 5</th>
<th>House 8</th>
<th>House 10</th>
<th>House 19</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>cumulative time use (in mins)</td>
<td>286</td>
<td>73</td>
<td>639</td>
<td>162</td>
<td>369</td>
</tr>
<tr>
<td></td>
<td>% of time spent on cooking over all inferred activities for this household</td>
<td>12.45%</td>
<td>4.25%</td>
<td>10.56%</td>
<td>9.58%</td>
<td>19.76%</td>
</tr>
<tr>
<td></td>
<td>Cumulative electricity consumed (kWh)</td>
<td>75.4</td>
<td>33.1</td>
<td>98.3</td>
<td>65.6</td>
<td>67.6</td>
</tr>
<tr>
<td></td>
<td>% of electricity consumed over all inferred activities for this household</td>
<td>22.33%</td>
<td>11.73%</td>
<td>15.45%</td>
<td>15.53%</td>
<td>16.21%</td>
</tr>
</tbody>
</table>

Cooking is the main energy-consuming activity. Houses 4 and 19 cook on a gas hob which reduces their electricity consumption for cooking activity.
Results: Time-use and electricity consumption of laundering across all households

- % of electricity consumed by laundering over all inferred activities for this household
- % of time spent on Laundering over all inferred activities for this household
Clear pattern observed: This household occupied by a retired couple spends most of their time watching TV during the evening, but still watched TV (a bit less) throughout the rest of the day.
In contrast, this family with two teenagers watches TV in the evenings primarily after a day at school, work and various after-school activities.
This house is occupied by a couple of pensioners. The household wakes up every day between 6-7am, and the TV is being left on throughout the day until the late night during weekdays. During weekends, on the other hand, there is markedly less TV watching, less computing, whereas time is allocated more to cooking and eating.
Results. Typical weekday and weekend activity time profiles within a house

• Shows routines for a family with two teenage children.
• Cooking shows marked variation from weekday to weekend, reflecting the changing domestic routines of a household with school age children and working adults not at home during weekdays. Cooking activities at the weekend are more frequent and of longer duration spread throughout the day).
Consumption Breakdown – House 8

- Two pensioners – Detached house
- Average monthly consumption: 420Kwh = £64.68 (unit price £0.154)

- The total electricity use explained by activity inferences is 33%. The rest is accounted for by lighting, cold appliances, base load, heating.
Activities can account for up to 44% of total electricity consumption—House 5.
Activity electricity consumption - House

- Cooking: 12%
- Laundering: 4%
- Watching TV: 4%
- Computing: 6%
- Hobbies: 0%
- Other: 74%

- Base load: 21%
- Cold appliances: 41%
- Unknown (inc. lighting): 12%
Conclusions

- Proposed a methodology that brings together qualitative and quantitative data to make inferences on daily activities in a household.
- Electricity consumption and time-use linked to activities in typical days, weekends, or monthly.
- Interesting to look at both time use and electricity consumption to understand eco-friendly behaviour or suggestions for retrofit.
- Detected activities can account for a significant percentage of energy consumption within households.
Proposed a useful tool for a range of applications:

1. Comparison with time use statistics
   -> *identification with national clusters*

2. Temporal stability and sequencing of activities
   -> *demand response*

3. Activity-based energy feedback
   -> *retrofit & energy savings*

4. Reduced methodology for smart meter rollout
   -> *real-time activity time profiles nationwide!"
Questions?

For more information
visit our website: www.refitsmarthomes.org
email: Lina Stankovic lina.stankovic@strath.ac.uk
Laundering duration and electricity consumption within a house totalled over a month
This household usually do the laundering around mid-night, compared with house 4, the house spent more time but consumed less energy than house 4.