Low-rate Energy Disaggregation: Lessons Learnt and Key Challenges for Widespread Adoption

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Motivation

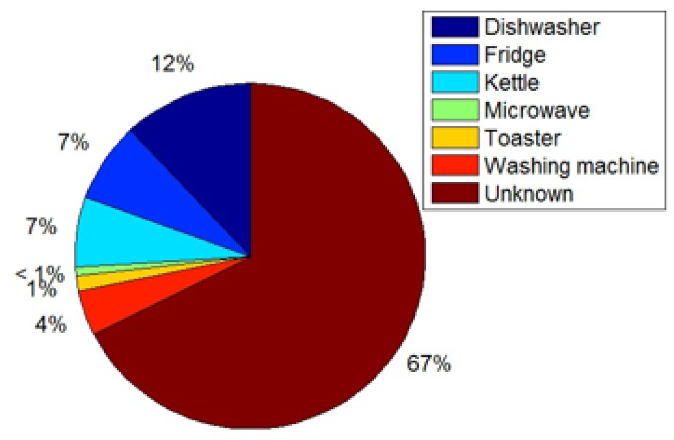
- Smart metering campaign underway across UK, EU and worldwide
  - 200Million smart meters to be deployed in EU (EUR45Billion investment)
- Huge expectations from the smart metering programme
  - Real-time, but limited, energy feedback via In Home Display
  - Estimated residential energy consumption reduction by 9%
  - Improved billing practices, i.e., more accurate, less estimated…
- …but there are many different views
  - 'Smart meters are poor value for the money' *Which? (2014)*
- How to maximise benefits of smart metering to the customer and make a return on investment?
- What do we do with all the smart meter data gathered?
- How do we extract meaningful information going beyond outage management, asset management and accurate billing?
- Smart meter data availability in EU, from 1-60sec to 15-60 mins granularity
- REFIT [1] + other electricity measurement datasets publicly available facilitate hands-on research on energy analytics and validation in realistic environment

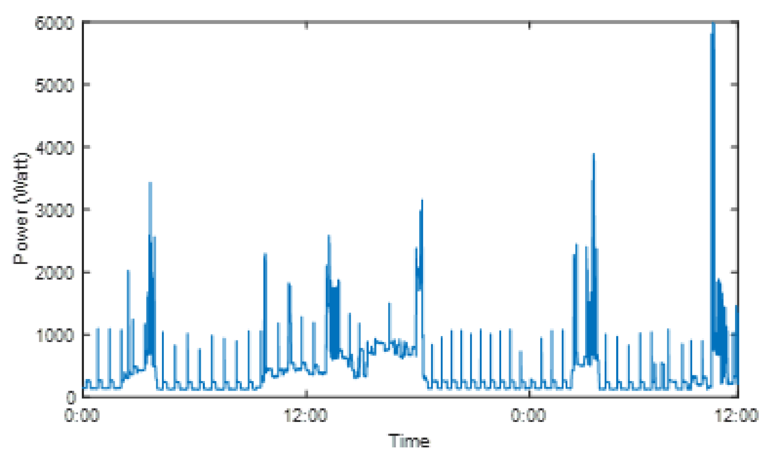
Energy Disaggregation

- Energy disaggregation or non-intrusive load monitoring (NILM) - means for converting smart meter data into actionable information
- NILM can lead to savings in the range of 1-4.5% -> 'Holy Grail' of energy efficiency (Armel et al., 2013)
- The impact of NILM if rolled-out at scale still unknown
- Currently, limited industrial offerings in the field: 50% EU-based, rest in North America mostly
  - Very few offer low (1sec) to very low rate (15-60 mins) NILM (mostly meter-agnostic)
  - Disaggregate high-load usage, e.g., water heaters, washing machines and dishwashers machines, HVAC, sometimes always-on/baseload, lighting, microwave

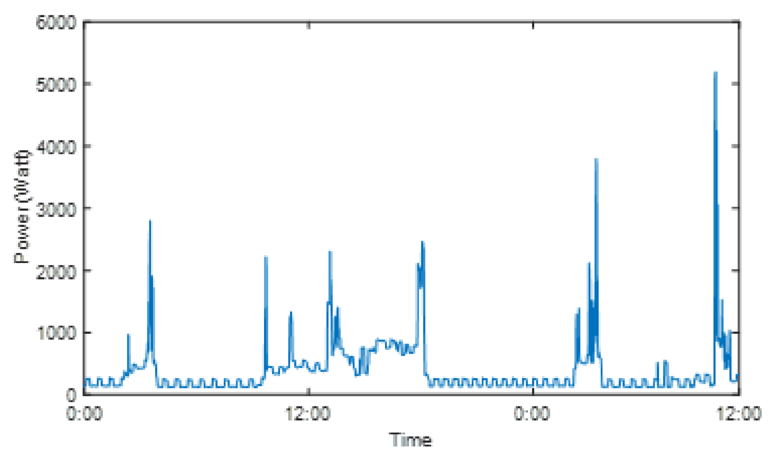
NILM: A challenging problem:

- Combinations of appliance, makes, models, and types
- Greater than 40 appliances per household
- Time fluctuations per appliance
- Different settings and usage scenarios lead to different load signatures
- Multi-state appliances
- Always on appliances with non periodic loads
- Simultaneous appliance usage

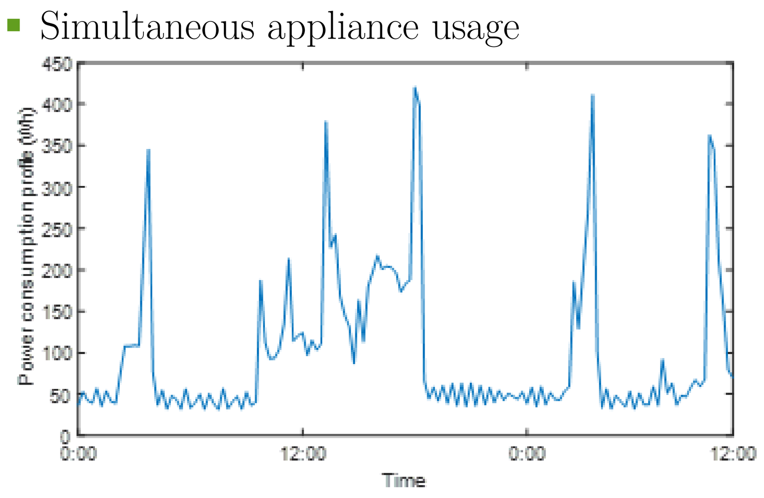




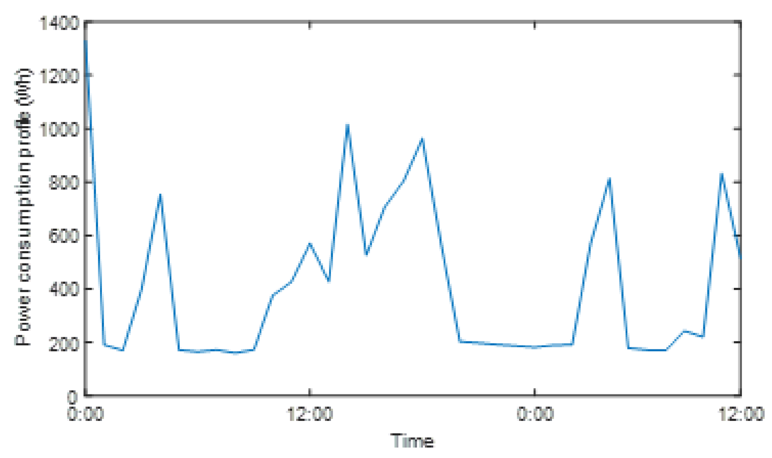
1 Second sampling rate



1 Minute sampling rate



15 Minutes sampling rate



1 Hour sampling rate

Real-time Monitoring → Data Cleaning → Data Management → NILM → Digital Analysis → Appliance Mining / Activity-based Feedback / Economy Wide Modelling

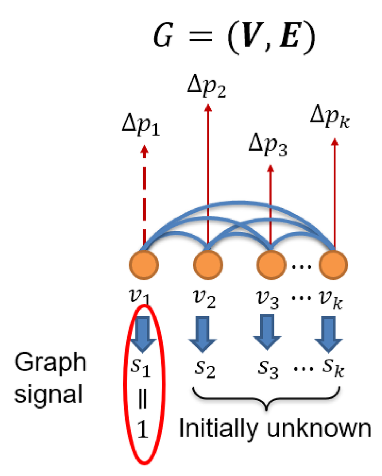
Supervised & Unsupervised NILM at Strath

Supervised methods include:
robust but require a period of sub-metering or accurate usage diaries

- Supervised Graph Signal Processing (SGSP) [2] (EPSRC REFIT)
- Decision Tree (DT) [3] (EPSRC REFIT)
- K-means with Support Vector Machine [4] (EPSRC REFIT)
- Deep Neural Networks [5] (H2020 SENSIBLE)
- Generic NILM post-processing [6] (H2020 SENSIBLE)

Unsupervised methods include:
do not require a labelled set of appliances for training

- Dynamic Time Warping (DTW) [7] (EPSRC REFIT)
- Unsupervised Graph Signal Processing (USGSP) [8] (EPSRC REFIT)



Very Low Rate Data (≥ 15 Minutes)

- Traditional NILM approaches not applicable
- Very few NILM 'solutions' in literature, e.g., sparse coding, convex optimisation, and K-NN [9]

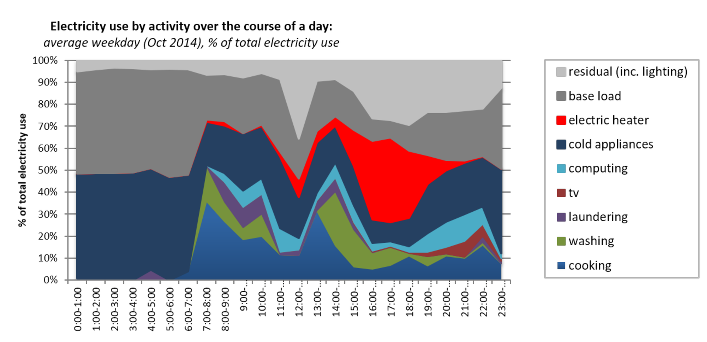
H2020 Eco-Bot Pilot Schemes @ scale:

- Business-Consumer - Residential, Spain (1 Hour)
  - 100 Households
- Business-Business - Non-domestic, EU inc. UK (15 Minutes)
  - 30 Commercial Buildings
- Business-Business-Consumer - Germany (10 Seconds)
  - 150 Households

eco-bot
let's talk energy!

Energy Demand & Feedback

- Understanding energy demand through activities [10]
- Personalised tariffs [11]
- Appliance modelling and informing energy savings [12]



Beyond Energy Feedback

- Quantifiable metrics of energy intensity and routine for comparison across households [10]
- Appliance/Food life cycle assessments [13]
- Load shifting [11]
- Load prediction [12]
- Computable general equilibrium (GCE) modelling with Int. Energy Agency (IEA)

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