Blind Non-intrusive Appliance Load Monitoring using Graph-based Signal Processing

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Motivation

- Large-scale smart meter deployments underway worldwide
- Huge investment
  - E.g., EUR35Billion in EU for installation of 200M smart meters
  - Consumers and government bear most of the cost
- Huge expectations…
  - Residential energy consumption reductions by 5-6%
  - Improved billing practices, i.e., more accurate, less estimated…
- … and many different views
  - "Smart meters are poor value for the money" *Which (2014)*
- How to maximize benefits of smart metering to the customer?

REFIT Project

Personalised Retrofit Decision Support Tools for UK Homes using Smart Home Technology

- *Consortium of three UK universities bringing together expertise in electrical engineering, civil engineering, design and social science*
- Deeper energy feedback through energy disaggregation
- New itemized billing practices (at appliance- and activity-level)
- Timely appliance retrofit advice
- Assessment of user interaction with smart automation technology
- New **open-source energy datasets** (electricity and gas, including quantitative and qualitative data)

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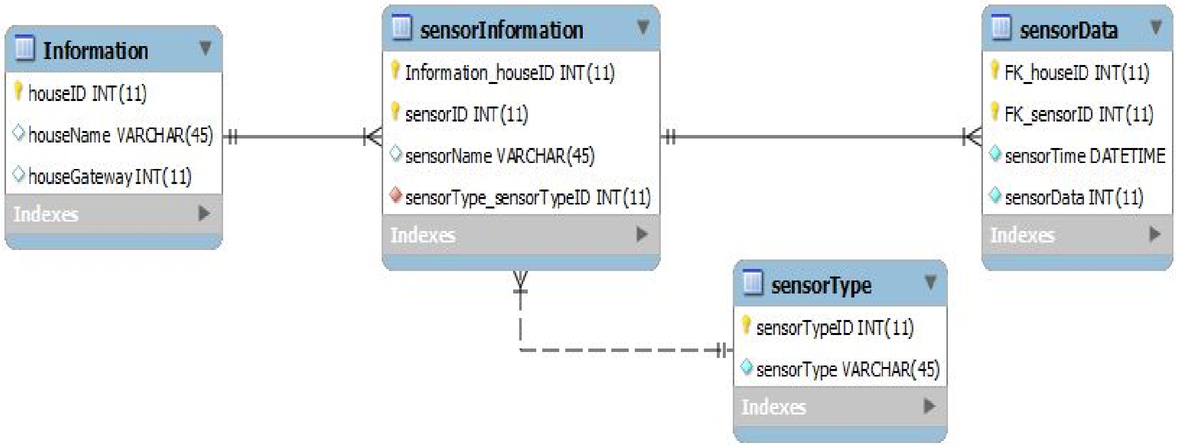
REFIT

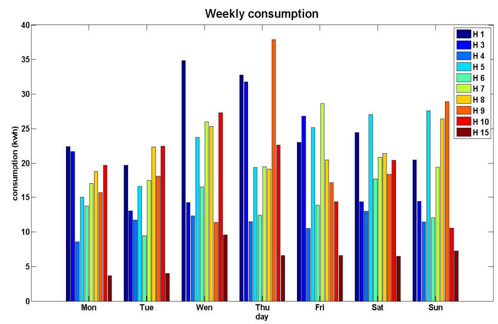
REFIT: SMART HOMES AND ENERGY DEMAND REDUCTION

EPSRC

Engineering and Physical Sciences Research Council

Real-time Data Acquisition Platform





Energy, Environmental & Occupancy Sensors → Real-Time Display → Gateway → Server Database → Data Checking & Cleaning → Statistical & Predictive Analysis

Open-source Dataset: goo.gl/QvQU4a

- Aggregate electricity data plus load data for 9 individual appliances (major consumers)
- 20 houses monitored for a period of 2 years
- Active power measured at 8secs sampling rate
- Additionally, a database of appliance signatures obtained via monitoring and crowdsourcing

D. Murray, L. Stankovic, V. Stankovic, et al, "Energy Reduction through the Use of Smart Home Appliance Monitoring and Feedback," *EEDAL-2015*

Non-intrusive Appliance Load Monitoring (NILM)

- Energy disaggregation from only aggregate active power
- Our focus on low sampling rates ~sec, mins

  [UK DECC: 10sec aggregate data available to the customer]
- Motivation: Develop a practical method that can work in any house without any:
  - Training
  - Consumer effort (e.g., taking a time diary, sub-metering, switching on/off appliances)

Problem Formulation

Disaggregate total energy consumption down to the individual appliances used

$$p(i) = \sum_{j=1}^{|\bar{\mathbf{M}}|} p_j(i) + n(i)$$

Find $p_j(i)$ for all appliances j and all time instances i, where

$p(i)$ – total active power at time instance i

$p_j(i)$ – power consumption of appliance j at time instance i

$\bar{\mathbf{M}}$ – a set of all known appliances

$n(i)$ – noise, including measurement noise and unknown appliances

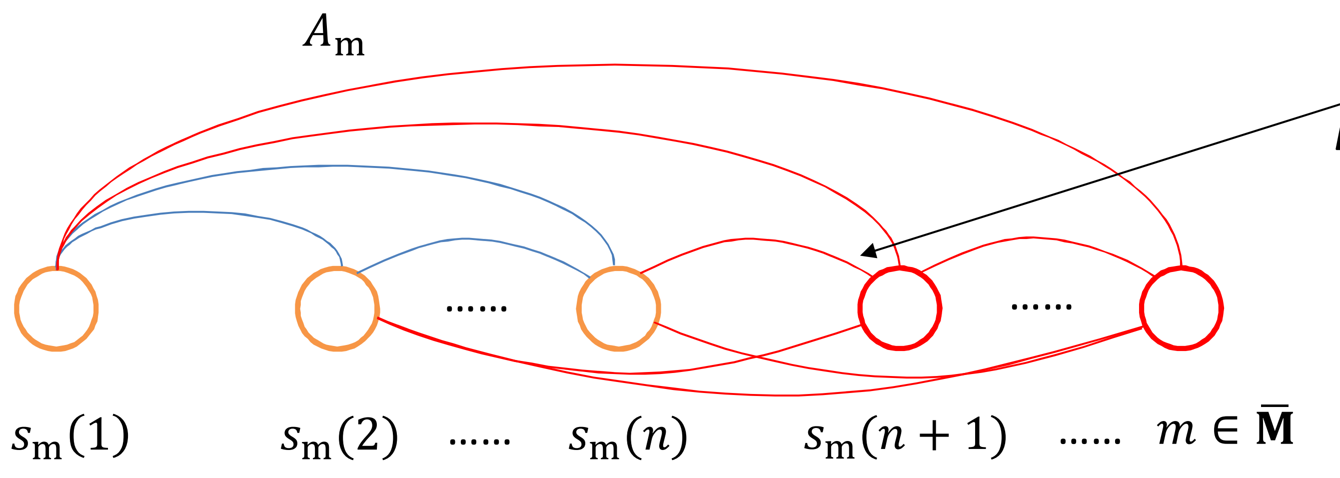
$$\Delta p(i) = p(i+1) - p(i) \;\;\&\;\; \Delta p_m(i) = p_m(i+1) - p_m(i)$$

Graph-based Signal Processing (GSP)

- *Embed the structure of the signal on to a graph*
- Represent a dataset by a discrete signal **indexed by a connected, undirected graph**
- **Signal samples** determine vertices of the graph
- **Weighted edges** capture correlation among samples
- Emerging field used in many signal processing problems, such as signal filtering, denoising, image compression, interpolation, etc.
- GSP-based supervised classification:
  - Based on the fact that if a signal is piecewise smooth, then the *total graph variation is generally small*
  - A robust approach able to deal with large and complex datasets

A. Sandryhaila and J. Moura, "Discrete signal processing on graphs," IEEE TSP-2013
C. Yang, G. Cheung, V. Stankovic, "Estimating heart rate via depth-based motion tracking," IEEE ICME-2015

GSP for Supervised NILM



For each appliance construct a graph and label it using training dataset $(i=1, \ldots, n)$

s_m: A set of nodes defined according to $\Delta p_m(i)$

$$S_m = \begin{cases} +1, & \text{for } \Delta p_m(i) \geq T \text{ and } i \leq n \\ -1, & \text{for } \Delta p_m(i) \leq T \text{ and } i \leq n \\ 0, & \text{for } i > n \end{cases}$$

T – small threshold used to detect events

A_{m}: weighted adjacency matrix, representing the correlation degree between two nodes, defined by Gaussian kernel weighting function:

$$A_m(i,j) = exp\left\{-\frac{(\Delta p(i) - \Delta p(j))^2}{\sigma^2}\right\}$$

σ is a heuristically chosen scaling factor

V. Stankovic, J. Liao, L. Stankovic, "A graph-based signal processing approach to low-rate energy disaggregation" IEEE SSCI-2014

Regularization on Graphs

fidelity term

smoothness term

Optimization problem:

$$\min_{p_m(i)} \left\| \Delta p(i) - \sum_{m\in\bar{\mathbf{M}}} \Delta p_m(i) \right\|_2^2 + \lambda \sum_{m\in\bar{\mathbf{M}}} \left\| {s_m}^T L_m s_m \right\|_2^2$$

L_m is a Laplacian matrix defined as: $L_m = D_m - A_m$

$D_m(k,k) = \sum_{j=1}^{N} A_m(j,k)$

- Minimizing smoothness term ${s_m}^T L_m s_m$ is an unconstrained quadratic programming problem with a closed form solution:

$$s_m^* = L_m(n+1{:}N, n+1{:}N)^{-1} * [(-s_m(1{:}n)^T) L_m(1{:}n, n+1{:}N)]^T$$

A.Sandryhaila and J. Moura, "Classification via regularization on graphs," IEEE GlobalSIP-2013

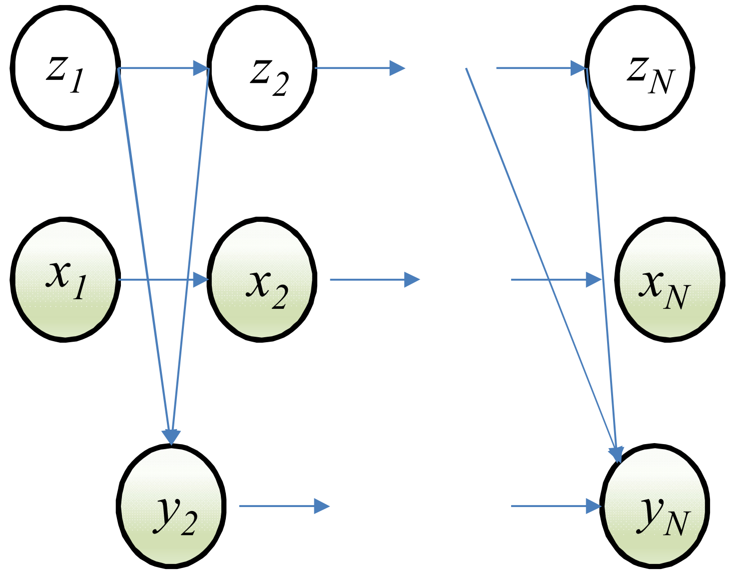
Classification Step

For $i > n$,

- If $s_m^*(i) \geq 0.5$, then the appliance m most likely has a state transition (e.g., on/off) at this time instance; then,
  - the corresponding $p_m^*(i)$ is set as the appliance's mean operating power estimated from training data
  - The contribution of this appliance is removed from the aggregate dataset.
- Otherwise, the appliance m most likely has no state transition and $p_m^*(i)$ is set as 0.

GSP vs Hidden Markov Model (HMM)

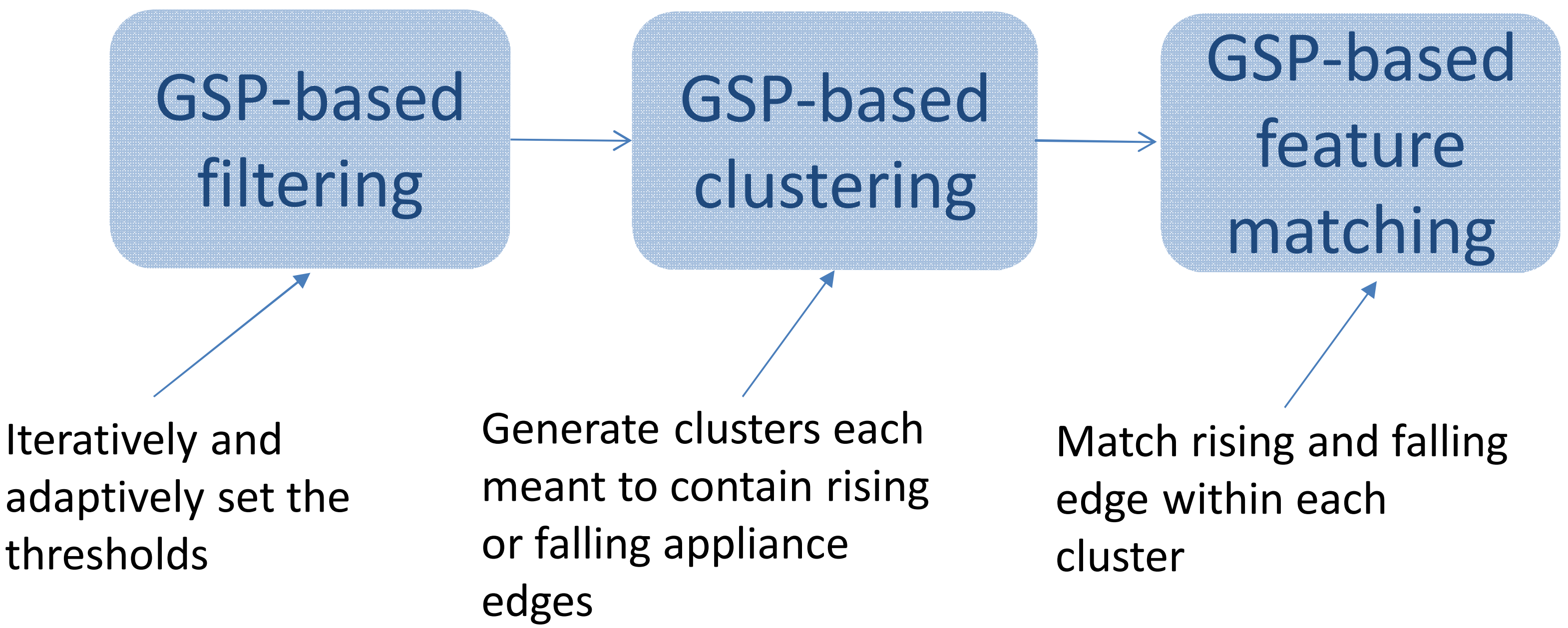
- HMM currently, THE most popular NILM method
  - Good amount of high quality observations needed to construct a graph
  - Good solution if observations are available and complexity not an issue

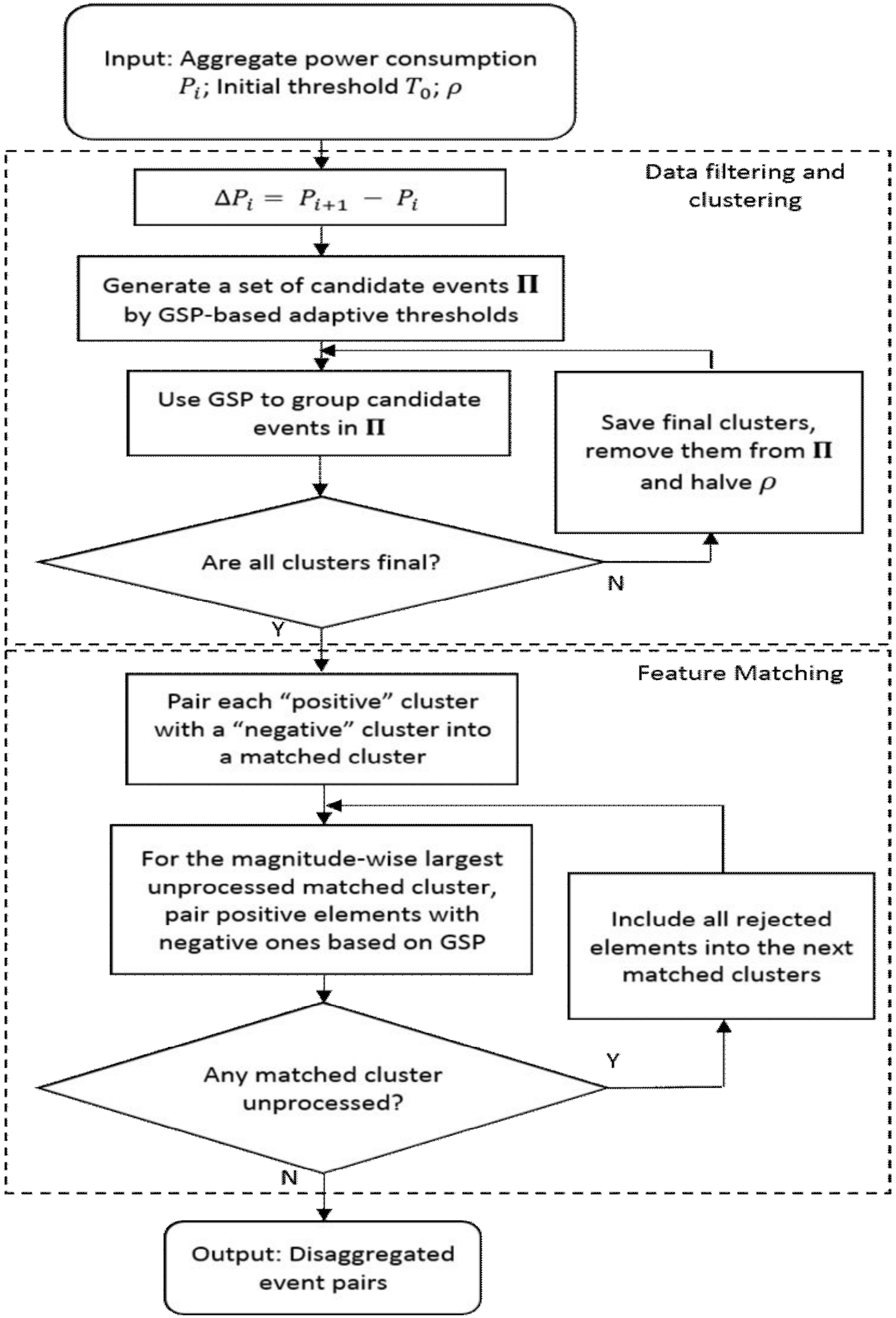


- GSP: a graph constructed in an intuitive manner, hence no need for probability state/transition estimates
  - Can be supervised, unsupervised, even training-less
  - Scalable and flexible, deterministic or probabilistic approach
  - Low-complexity, even with a large amount of data

Proposed GSP-based NILM Approach

- Unsupervised approach that **does not require any training**
- GSP used **three** times:





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Datasets and Evaluation Metrics

- Two datasets of active power readings for demonstration:
  - the REDD public datasets (http://redd.csail.mit.edu/) down-sampled to 1 minute;
  - the REFIT dataset (goo.gl/QvQU4a), sampled at 8 seconds.

Evaluation Metrics	Definition
Accurate True Positive (*ATP*)	correct claim the detected appliance was running and the corresponding events are correctly named
Inaccurate True Positive (*ITP*)	correct claim the detected appliance was running but the corresponding events are incorrectly named
False Positives (*FP*)	incorrect claim that the detected appliance was not running
False Negatives (*FN*)	the appliance operation was not detected
Precision(*PR*)	$PR = ATP/(ATP + FP)$
Recall(*RE*)	$RE = ATP/(ATP + ITP + FN)$
F-Measure(F_M)	$F_M = 2\cdot (PR \cdot RE)/(PR + RE)$

Performance Results

Appliance	*ATP*	*ITP*	*FP*	*FN*	*PR*	*RE*	F_M
Microwave	10	0	3	0	0.77	1	0.87
Toaster	4	1	3	3	0.57	0.5	0.53
Stove	7	5	3	2	0.7	0.5	0.58
Refrigerator	439	8	56	132	0.89	0.76	0.82
Dishwasher	26	6	61	5	0.3	0.7	0.42
Heater	3	0	56	3	0.05	0.5	0.09
AC	44	9	0	1	1	0.81	0.9
Light	7	6	7	12	0.5	0.28	0.36
Unknown	146	6	56	65	0.72	0.67	0.69

House 6 from the REDD dataset (1 min)

Appliance	*ATP*	*ITP*	*FP*	*FN*	*PR*	*RE*	F_M
Microwave	7	10	0	3	1	0.35	0.52
Toaster	4	1	2	1	0.67	0.67	0.67
Kettle	39	7	6	2	0.87	0.81	0.84
Refrigerator	18	0	2	0	0.9	1	0.95
Freezer	54	16	180	24	0.23	0.57	0.32
TV	4	0	180	6	0.02	0.4	0.04
WM	3	1	8	0	0.27	0.75	0.4

House 8 from the REFIT dataset (8 sec)

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Performance Comparison

Appliance	House 2			House 6		
	F_{M_U}	F_{M_S}	F_{M_H}	F_{M_U}	F_{M_S}	F_{M_H}
Microwave	0.94	0.26	0.47	0.87	0.92	0
Toaster	0.73	0.59	0.68	0.53	1	0
Stove	0.25	0.41	0.21	0.58	1	0
Refrigerator	0.78	0.63	0.9	0.82	0.54	0.88
Dishwasher	0.77	0.56	0.04	0.42	-	-
Heater	-	-	-	0.09	0.11	0.03
AC	-	-	-	0.9	0.49	0.12

REDD dataset. F_{M_U}, F_{M_S} and F_{M_H}: the proposed approach, [1] and [2], respectively.

Appliance	House 8			House 10		
	F_{M_U}	F_{M_S}	F_{M_H}	F_{M_U}	F_{M_S}	F_{M_H}
Microwave	0.52	0.47	0.46	-	-	-
Toaster	0.67	0.6	0.26	-	-	-
Kettle	0.84	0.92	0.55	-	-	-
Refrigerator	0.95	0.22	-	0.53	0.43	0.34
Dishwasher	-	-	-	0	0.63	0.44
Washing Machine	0.4	0.67	-	0.96	0	-
Freezer	0.32	0.58	-	0.49	0.35	0.34

REFIT dataset. F_{M_U}, F_{M_S} and F_{M_H}: the proposed approach, [1] and [2], respectively.

[1] V. Stankovic, J. Liao, and L. Stankovic, "A graph-based signal processing approach for low-rate energy disaggregation," in *Proc. IEEE Symposium Series on Computational Intelligence (SSCI)*, Orlando, FL, December 2014.
[2] O. Parson, S. Ghosh, M. Weal, and A. Rogers, "Non-intrusive load monitoring using prior models of general appliance types," in *Proc. The 26th Conf. Artificial Intelligence (AAAI-12)*, Toronto, CA, July 2012.

Conclusions

- A NILM approach proposed that does not require any training
- Besides the refrigerator, both GSP-based approaches perform significantly better than the HMM-based approach
- The proposed training-less GSP-based NILM approach is competitive to the supervised GSP-based NALM approach
- Future Directions:
  - Determine performance limits of the proposed scheme (submitted Dec.2015)
  - Efficient implementation of the approach as part of a decision support system
  - Application to other demand management tasks, such as demand prediction and load profiling