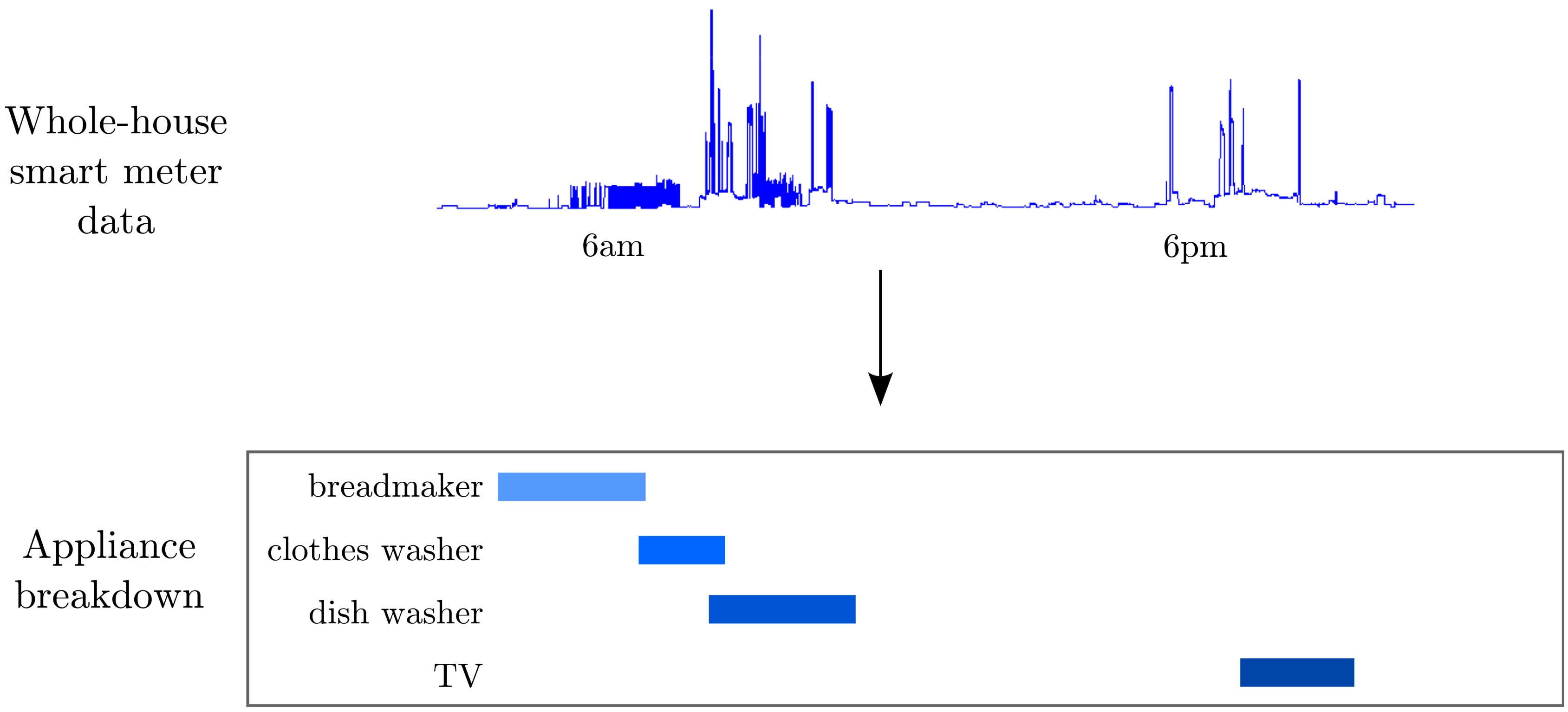
Disaggregating multi-state appliances from smart meter data

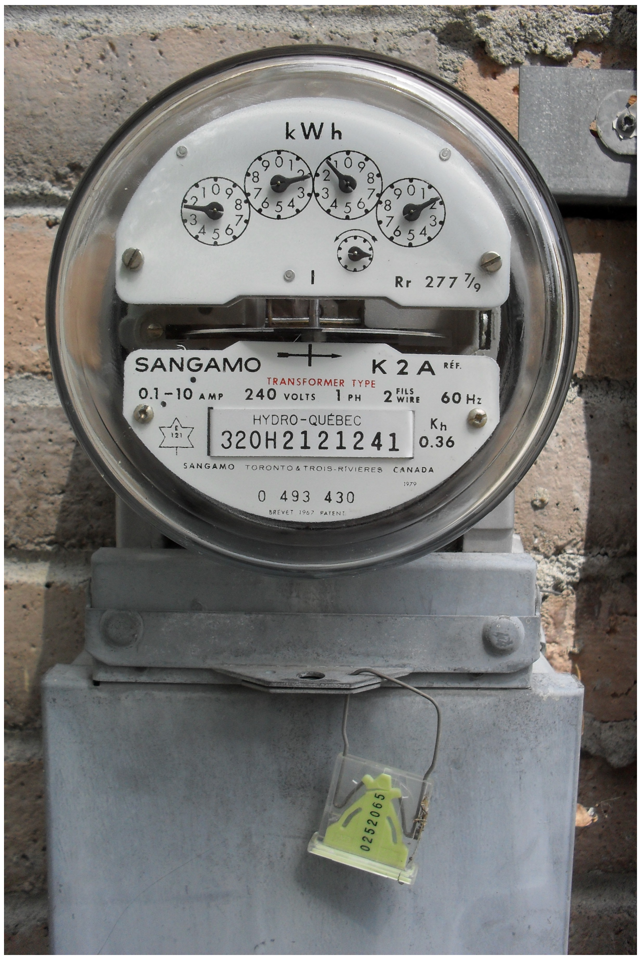


Daniel “Jack” Kelly
Imperial College (started PhD in October 2011)
daniel.kelly10@imperial.ac.uk

Outline

1. Introduce the disaggregation problem
2. Challenges
3. Review two existing approaches
4. Describe my research plan

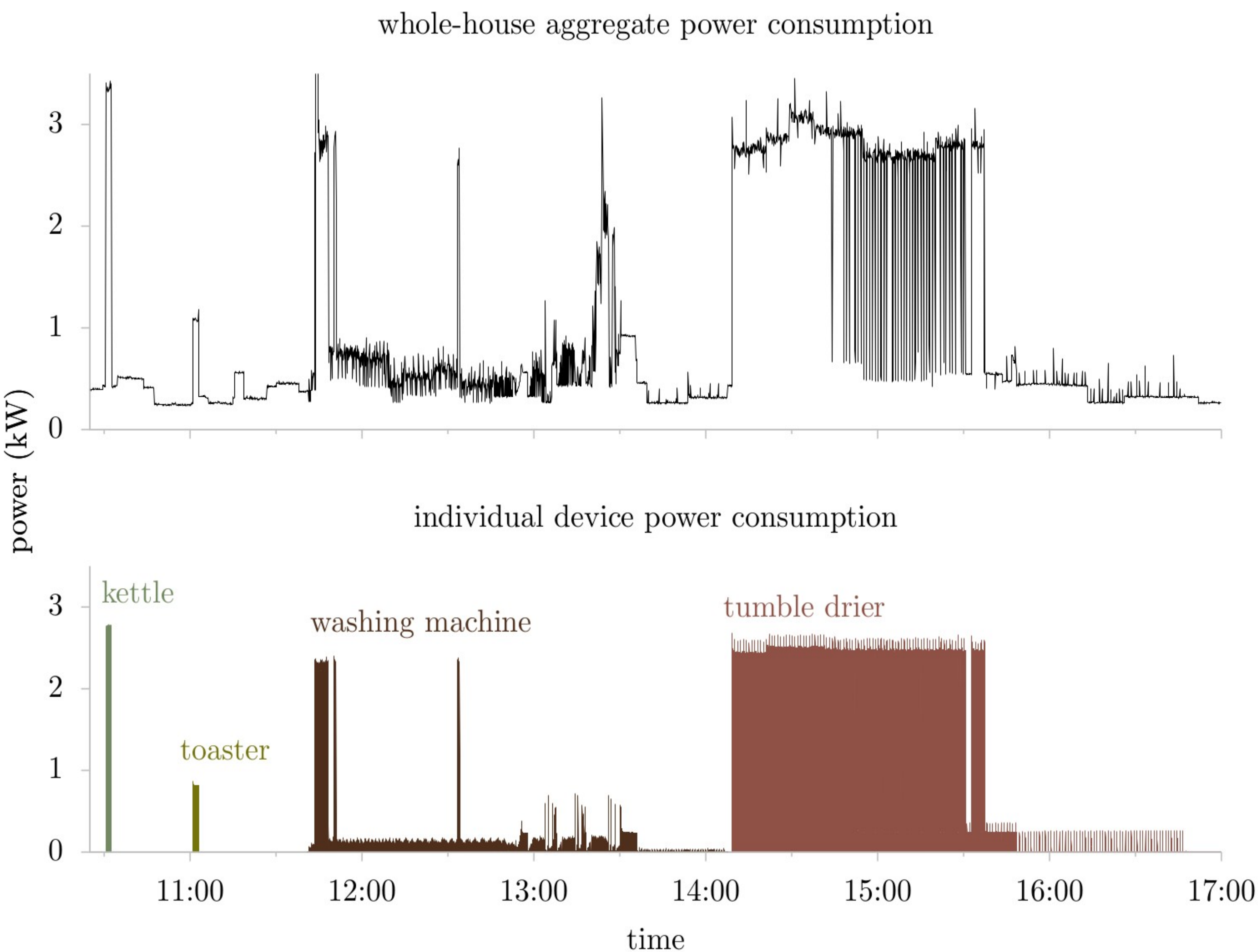
Existing electricity meter:



UK government have mandated that every home & business will have a smart meter by 2019 (that's 53 million meters):

British Gas are on schedule to have 2 million installed by the end of 2012

Home energy monitors


whole-house aggregate power consumption
individual device power consumption
power (kW)
kettle
toaster
washing machine
tumble drier
0
1
2
3
11:00
12:00
13:00
14:00
15:00
16:00
17:00
time

Reducing electricity consumption through smart meter feedback

- Energy use can differ by a factor of 3 among identical homes with similar appliances, occupied by people from similar demographics. (*Socolow 1978, Winett & Neale 1979, Seryak & Kissock 2003*)

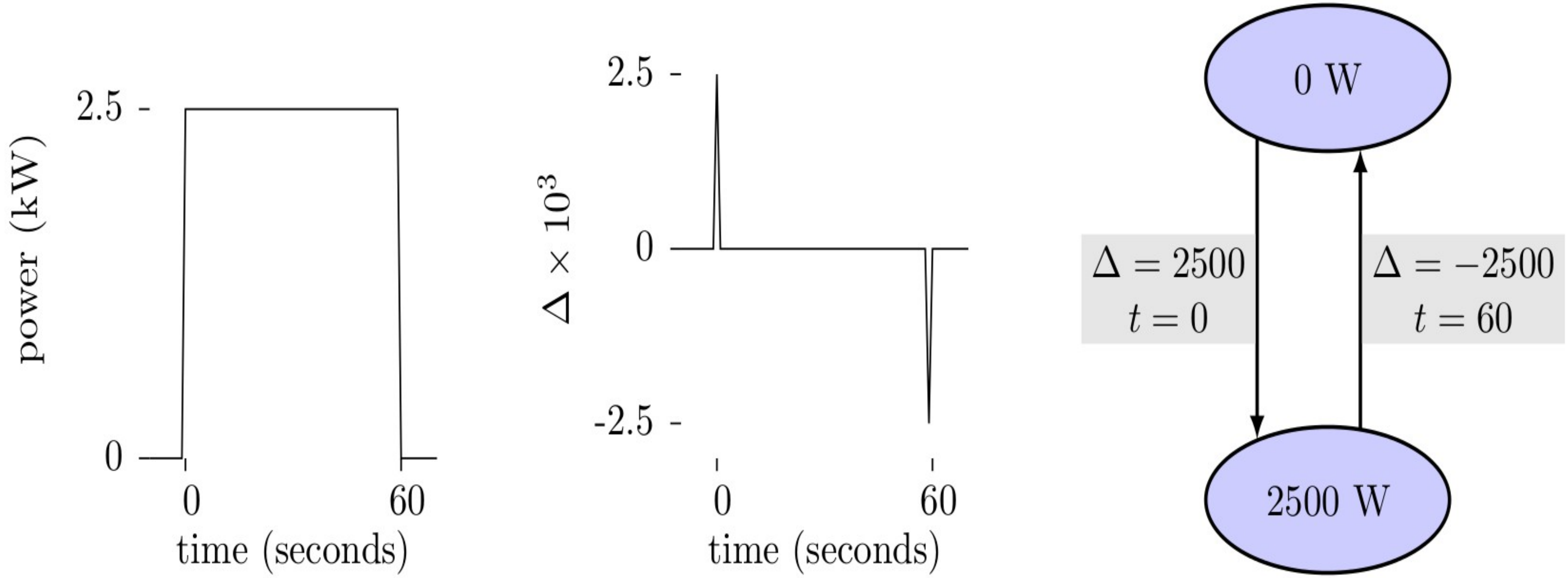
- Fischer (2008) reports: "*the most successful feedback combines the following features: it is given frequently and over a long time, provides an appliance-specific breakdown, is presented in a clean and appealing way, and uses computerised and interactive tools*."

- Direct feedback normally reduces energy consumption by 5-15% (*Darby 2006*).

- If every household reduced by 10% then 6 power stations could be closed, reducing the UK's annual CO_2 output would be reduced by 6 million tonnes

Some challenges

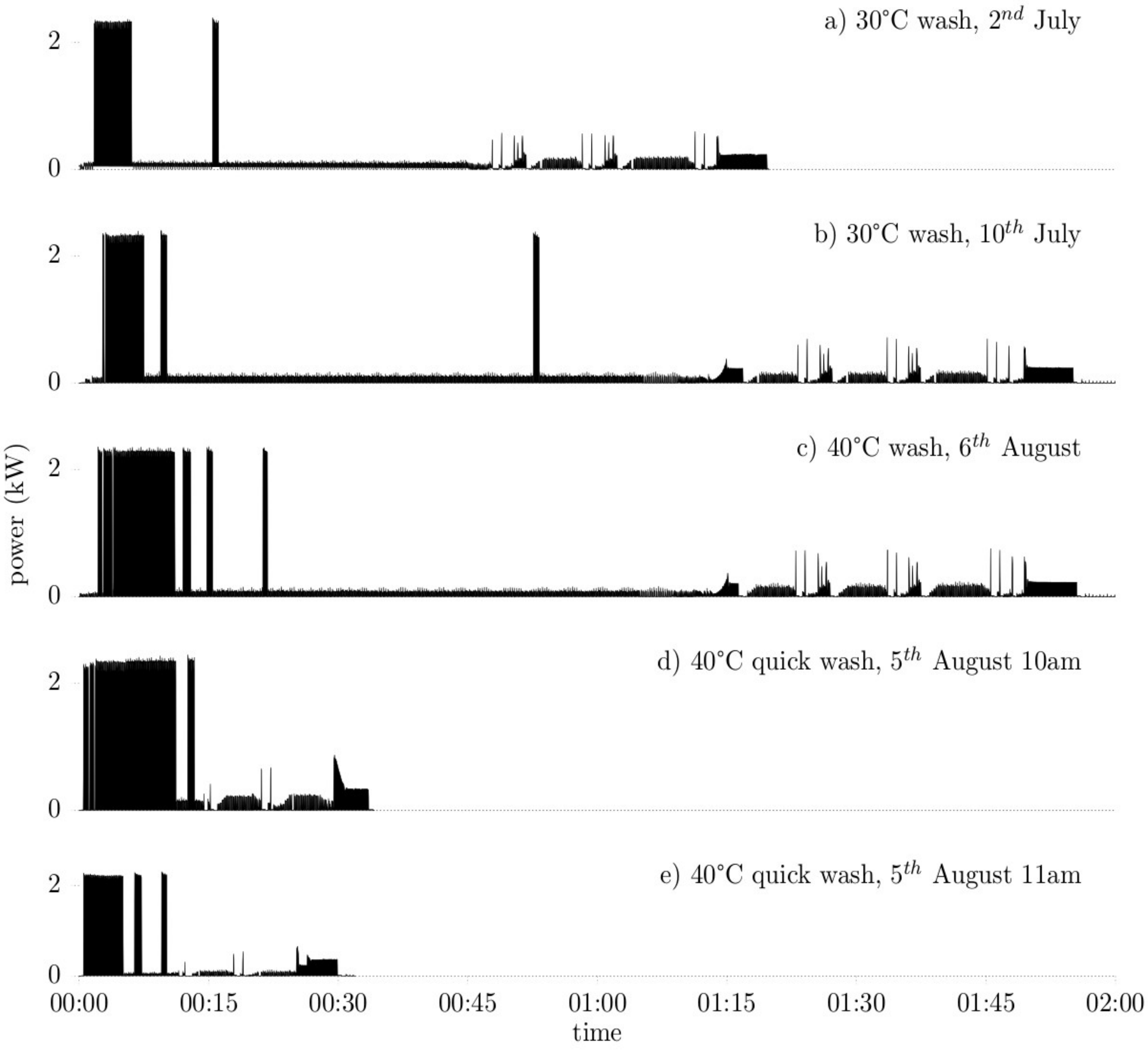
A toy example: modelling a kettle



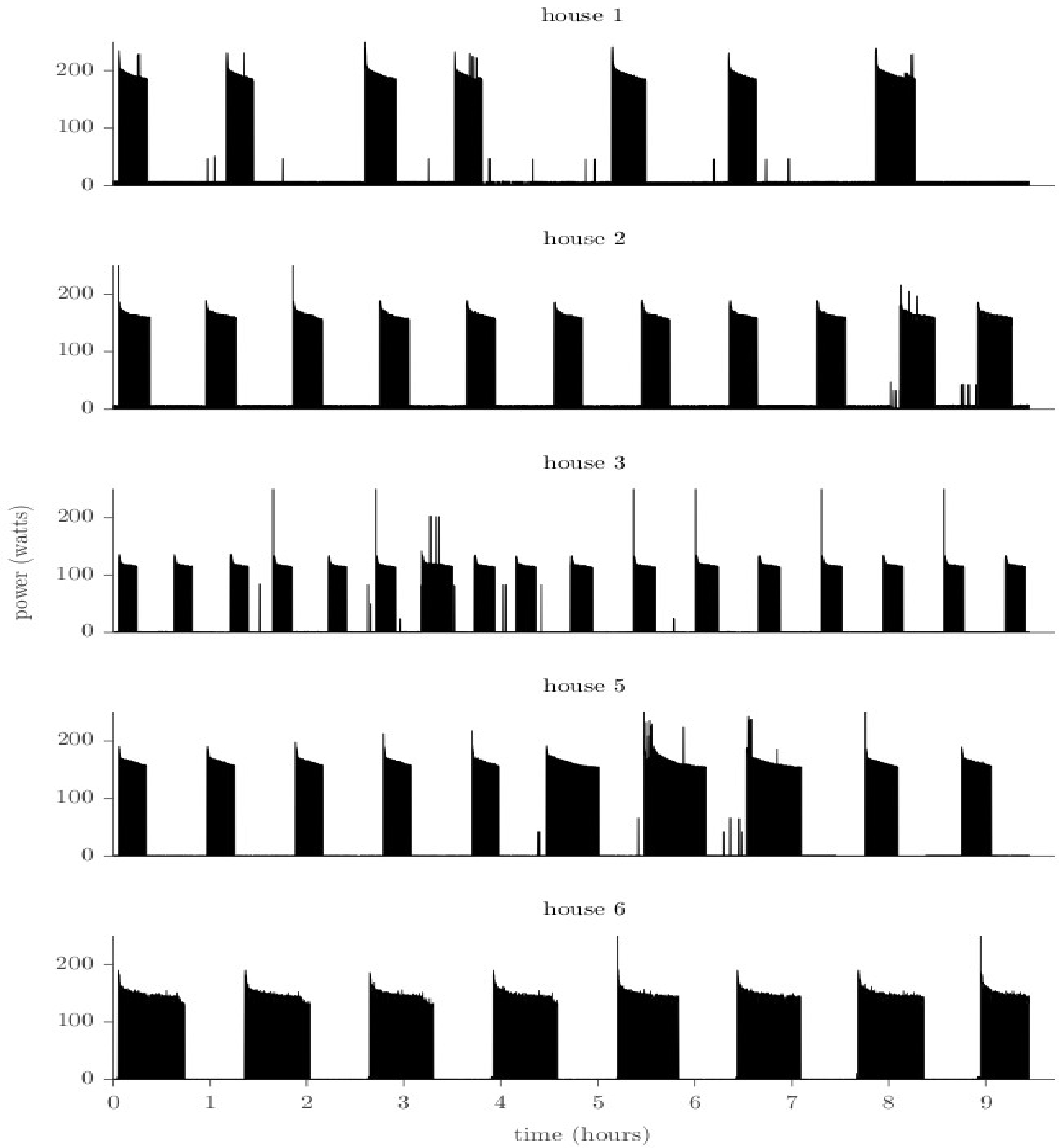
(a) (b) (c)

Most appliances are not as simple as a kettle....

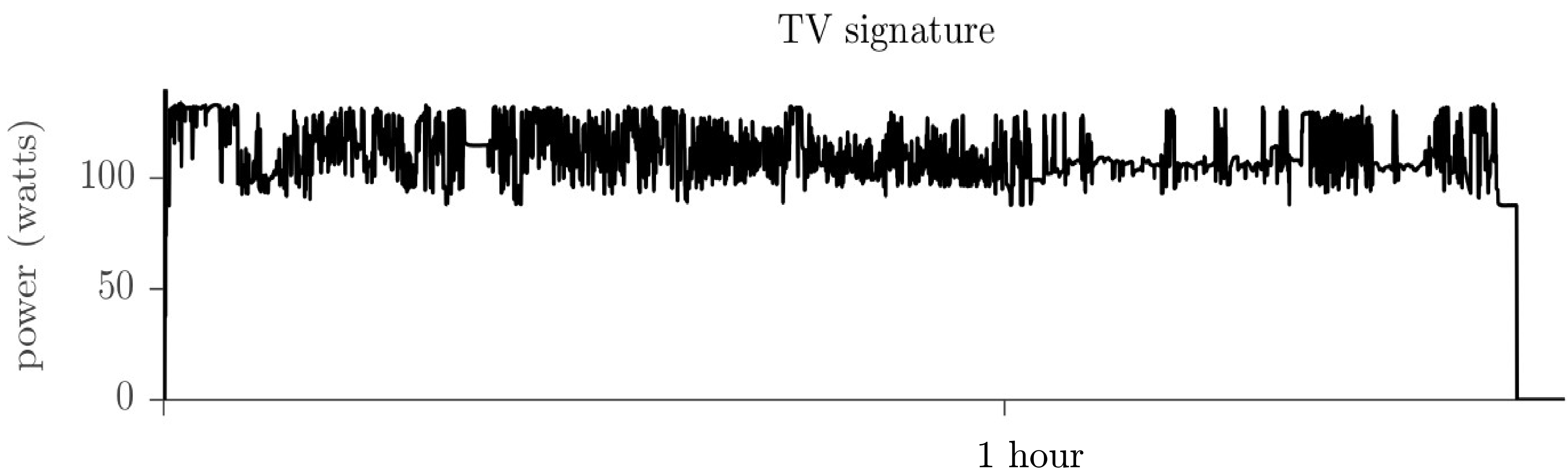
5 runs of the same washing machine:



5 different fridges



data from MIT's REDD dataset


TV signature
power (watts)
100
50
0
1 hour

Summary of some challenges:

Variation between:

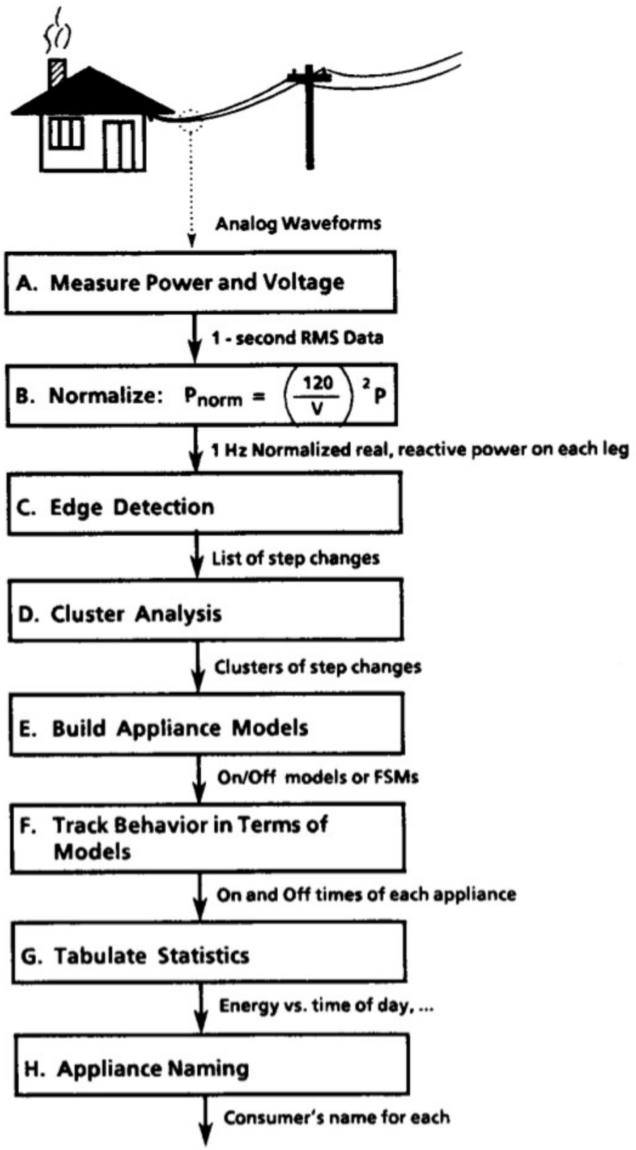
- devices of same class
- runs of same device in the same mode
- runs of the same device in different modes

Disaggregation research in the 1980s

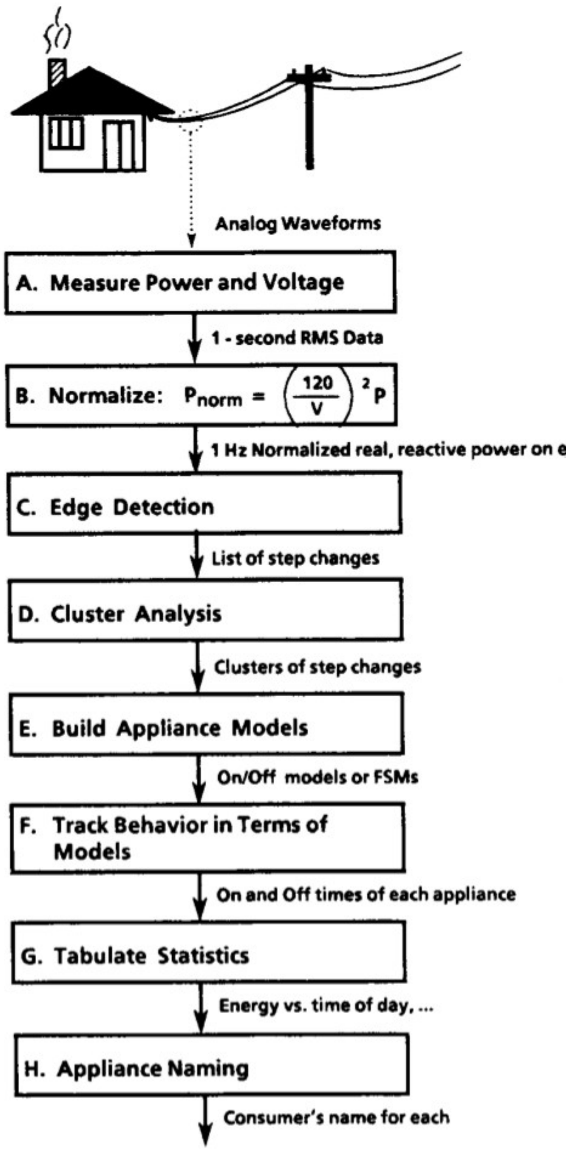
- Work done primarily by George Hart from 1984-95. Started at the MIT Energy Lab in the 80s and moved to the Electric Power Research Institute.

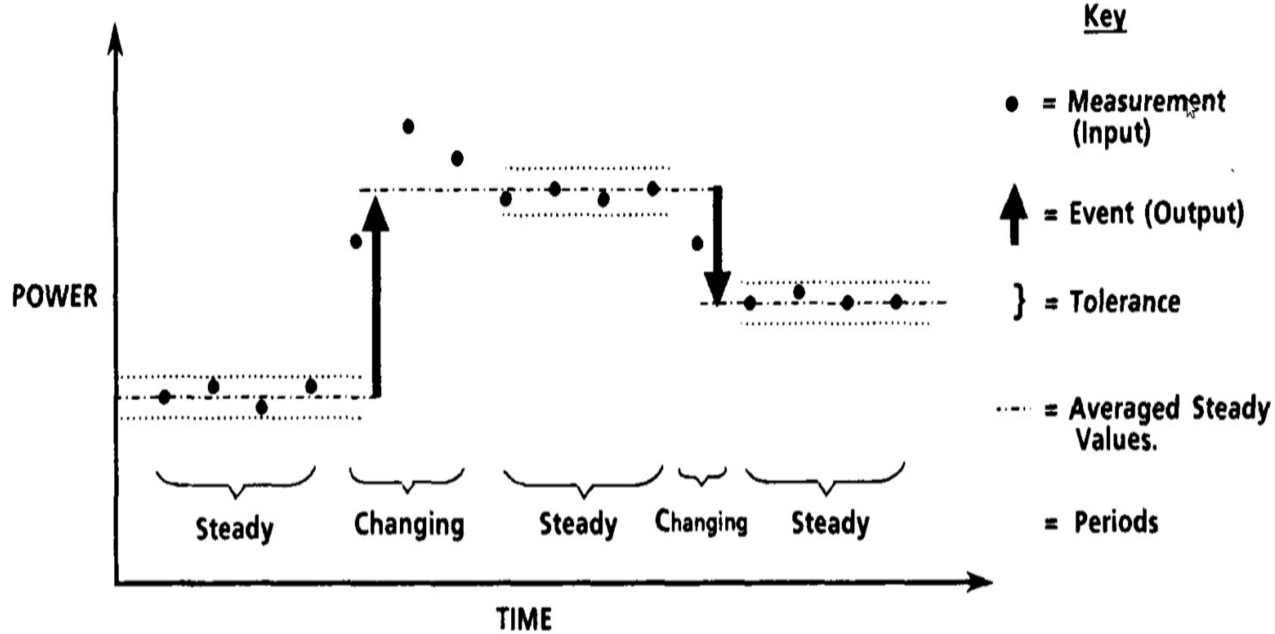
G. W. Hart, ‘Nonintrusive appliance load monitoring’, Proceedings of the IEEE, vol. 80, no. 12, pp. 1870-1891, Dec. 1992.

Hart's algorithm

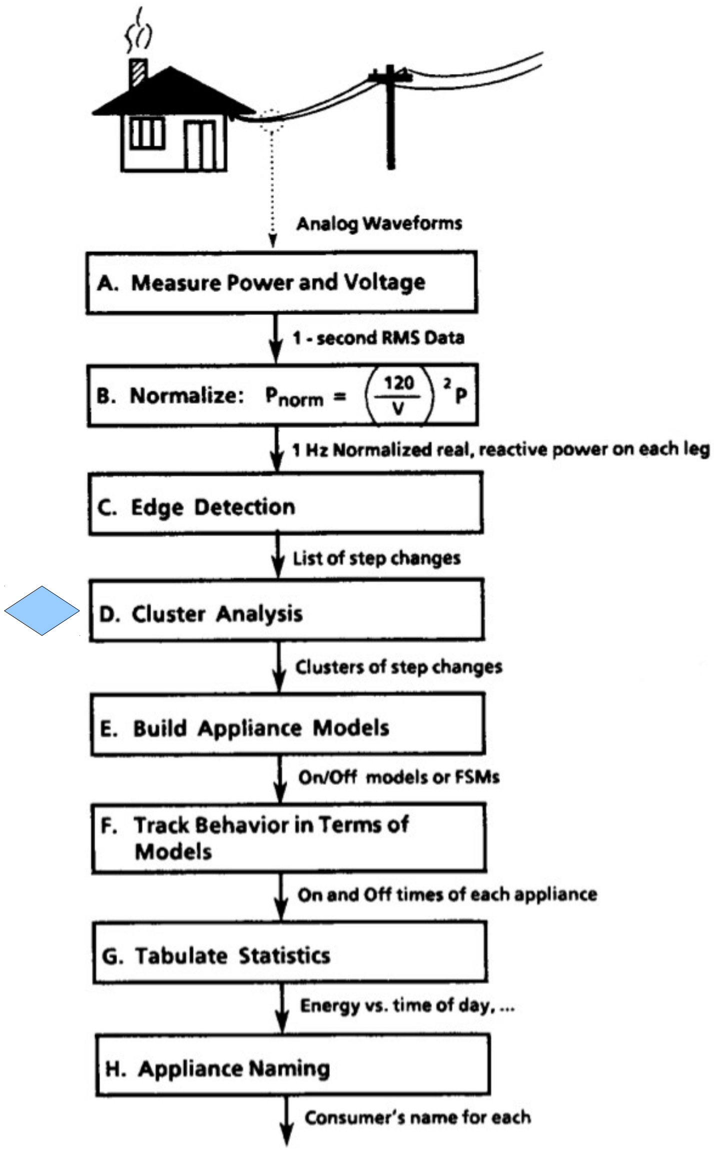


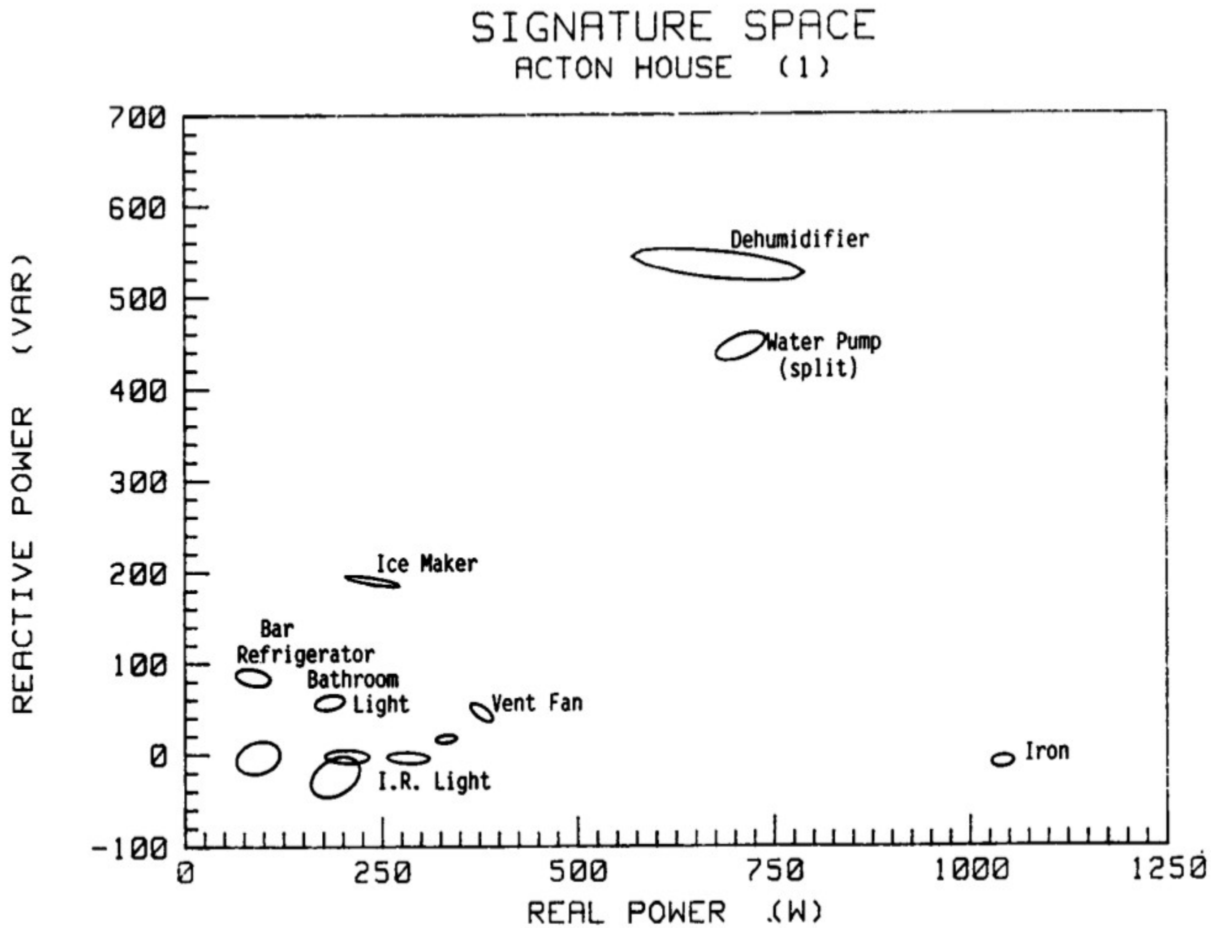
Hart's algorithm: Edge detection



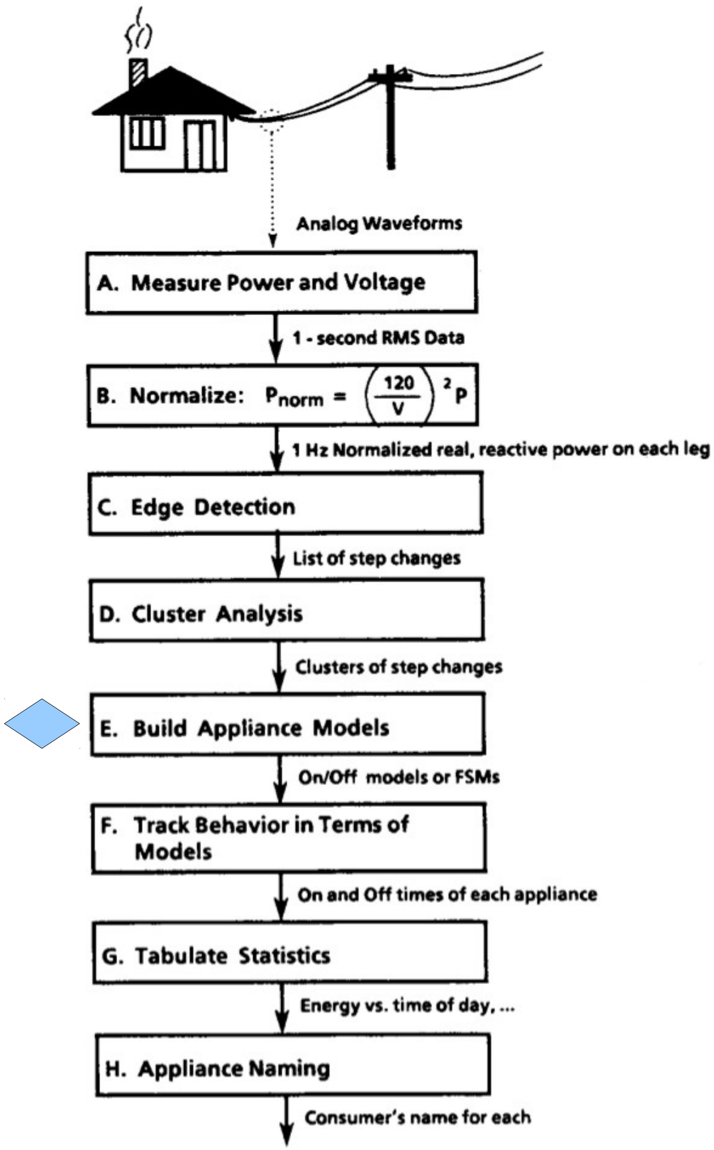


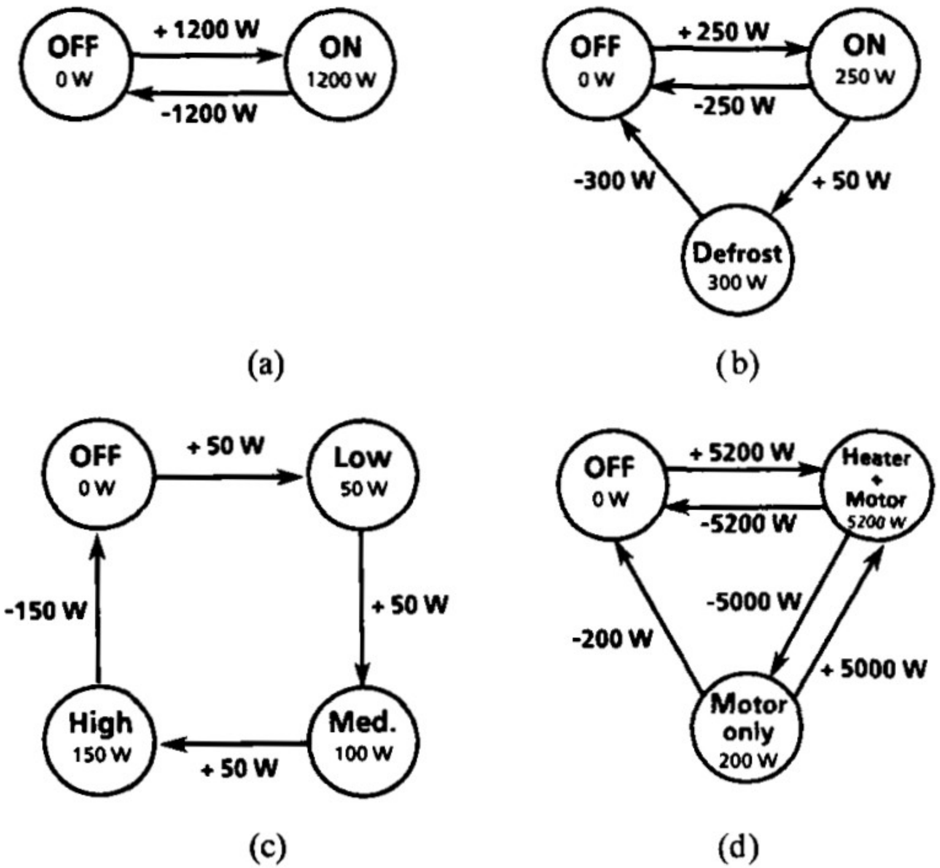
Hart's algorithm: clustering





Hart's algorithm: Models





Finite-state appliance models: (a) generic 1200 W two-state appliance, e.g., toaster; (b) refrigerator with defrost state; (c) "three-Way" lamp; (d) clothes dryer.

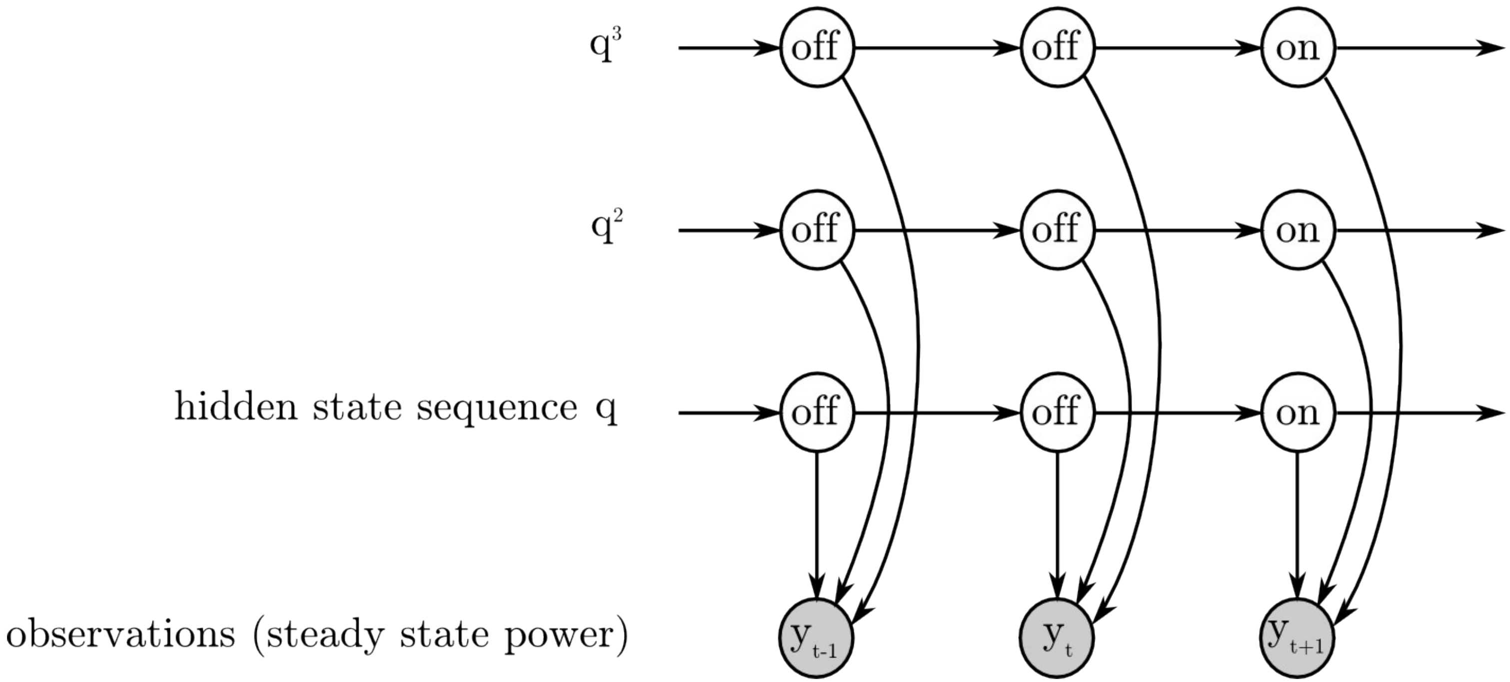
Performance of Hart's algorithm

- Field trial using 26 sites (total of 128 appliances)
- Two-state ('on' or 'off') loads detected with around 90% accuracy
- Refrigerators in the mid-80% range
- Multi-state appliances (e.g. dishwashers, clothes washers etc) registered “lower results”

“Although [Hart's algorithm is] effective as a load research tool for single-state appliances, ***enhancements must be made to the [disaggregation] algorithm to improve the monitoring for multi-state appliances and variable-speed loads.*** *Without the ability to monitor all types of appliances within a residence, [Hart's algorithm] does not provide a full-featured monitoring system.“*

Paragon, ‘Low-Cost NIALMS Technology: Technical Assessment’, Electric Power Research Institute, 1998.

Factorial Hidden Markov Model

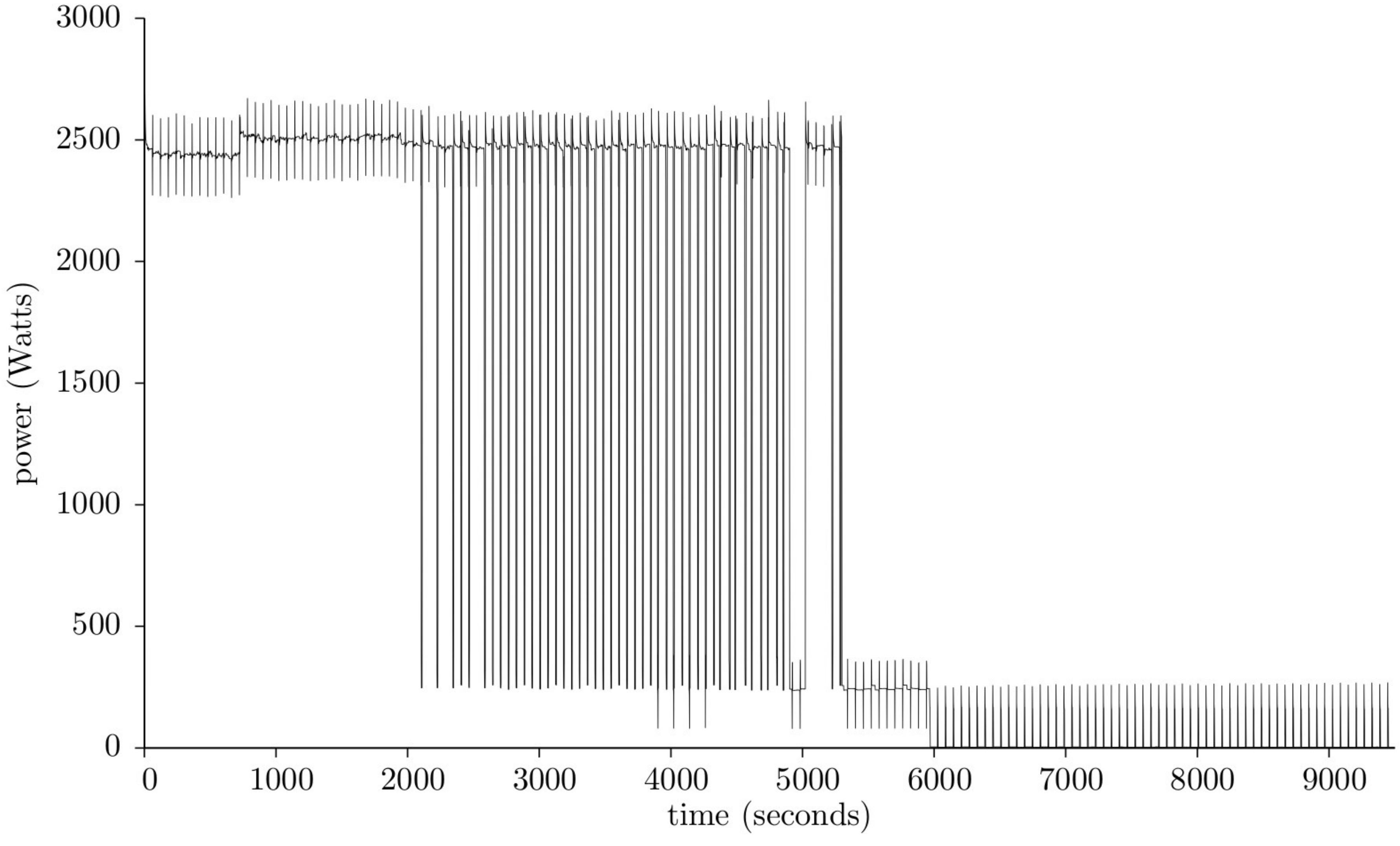


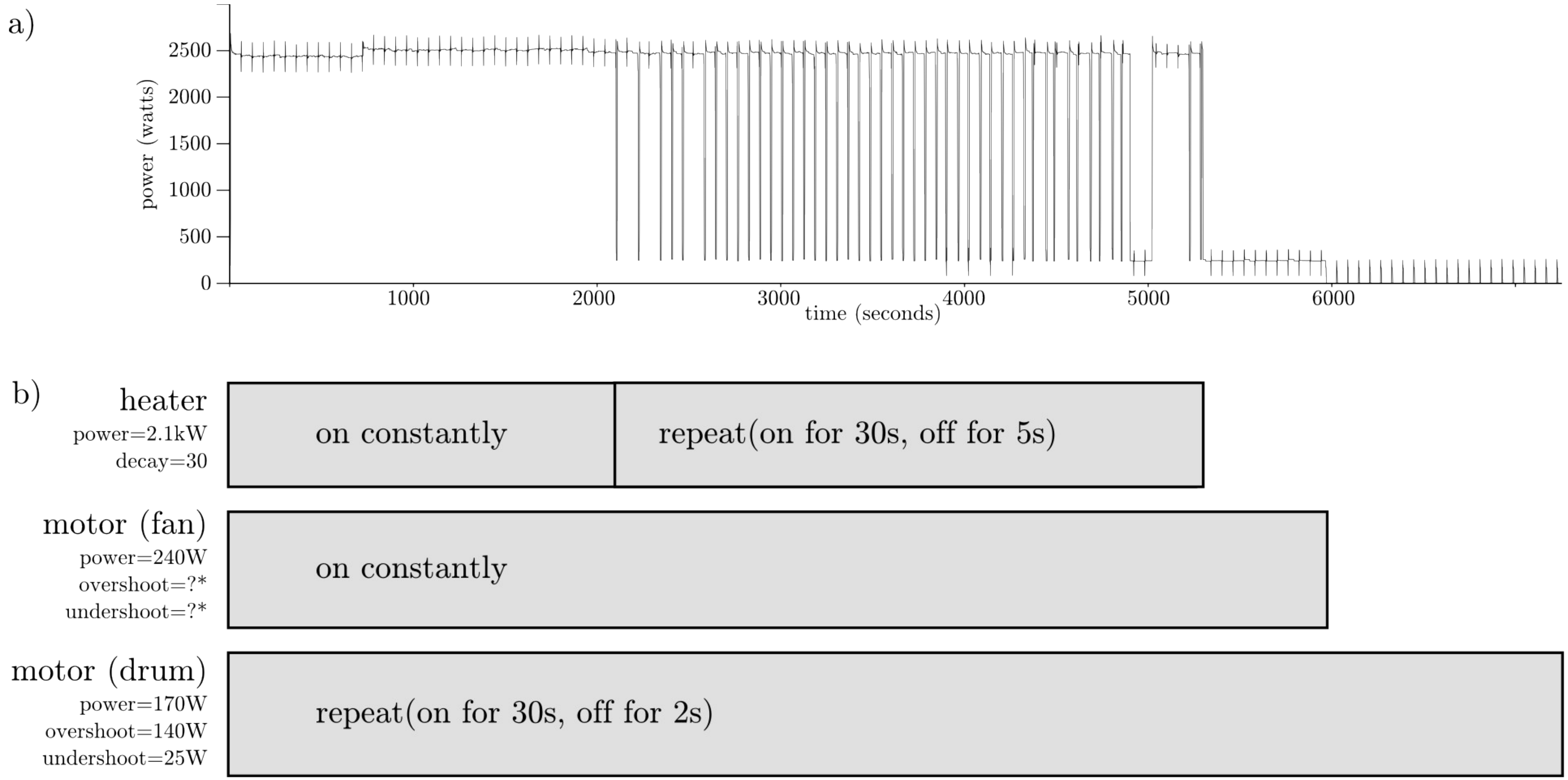
e.g.
•Kolter & Jaakkola 2012
•Kim *et al* 2011
•Parson *et al* 2012

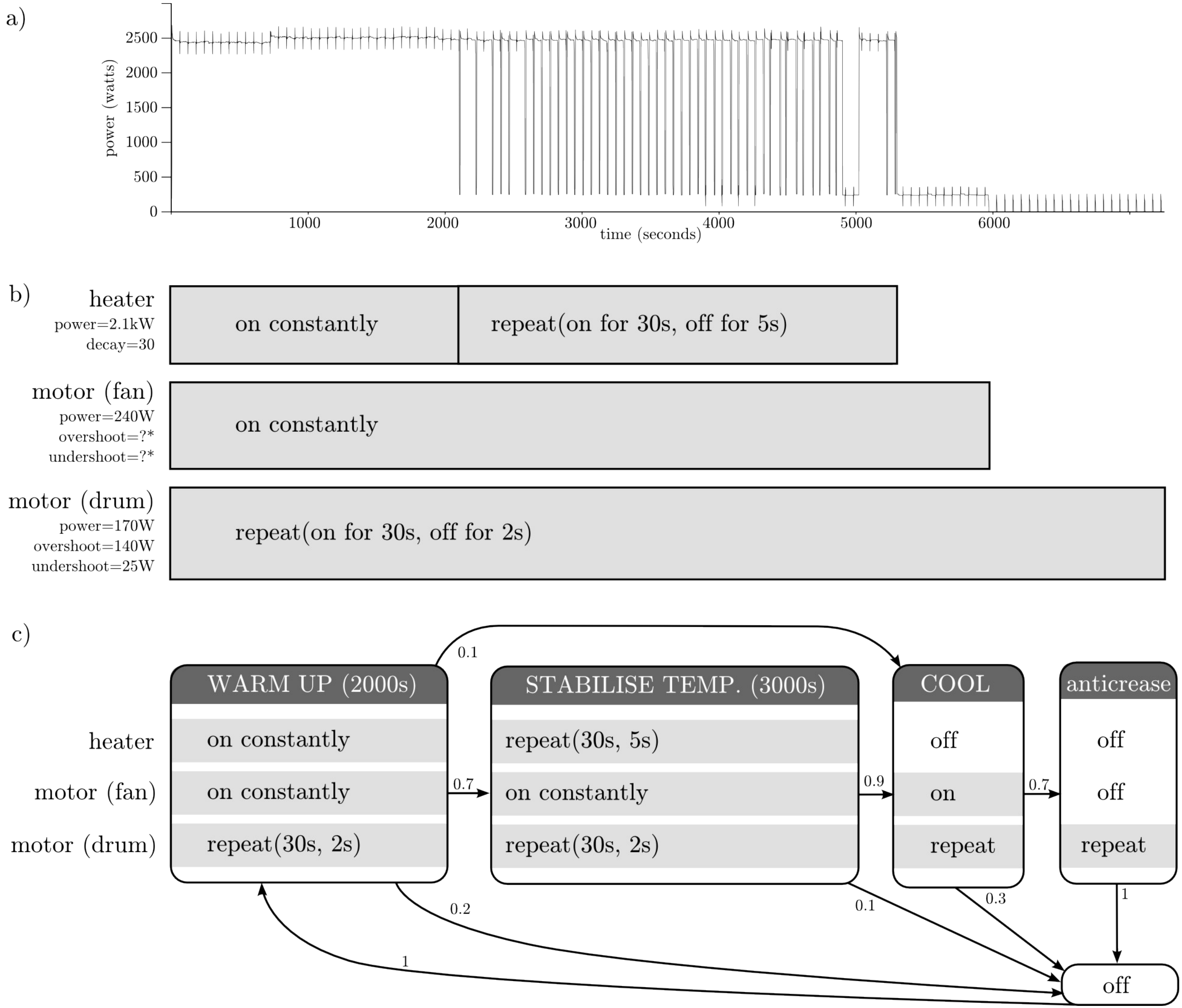
Research plan

- Plan to focus on two of the outstanding problems from the literature:
  1) modelling multi-state appliances
  2) take advantage of more features in the smart meter signal

Peering *inside* appliances




a)
2500
2000
1500
1000
500
0
power (watts)
1000
2000
3000
4000
5000
6000
time (seconds)
b)
heater
power=2.1kW
decay=30
on constantly
repeat(on for 30s, off for 5s)
motor (fan)
power=240W
overshoot=?*
undershoot=?*
on constantly
motor (drum)
power=170W
overshoot=140W
undershoot=25W
repeat(on for 30s, off for 2s)



a)
power (watts)
2500
2000
1500
1000
500
0
1000
2000
3000
4000
5000
6000
time (seconds)
b)
heater
power=2.1kW
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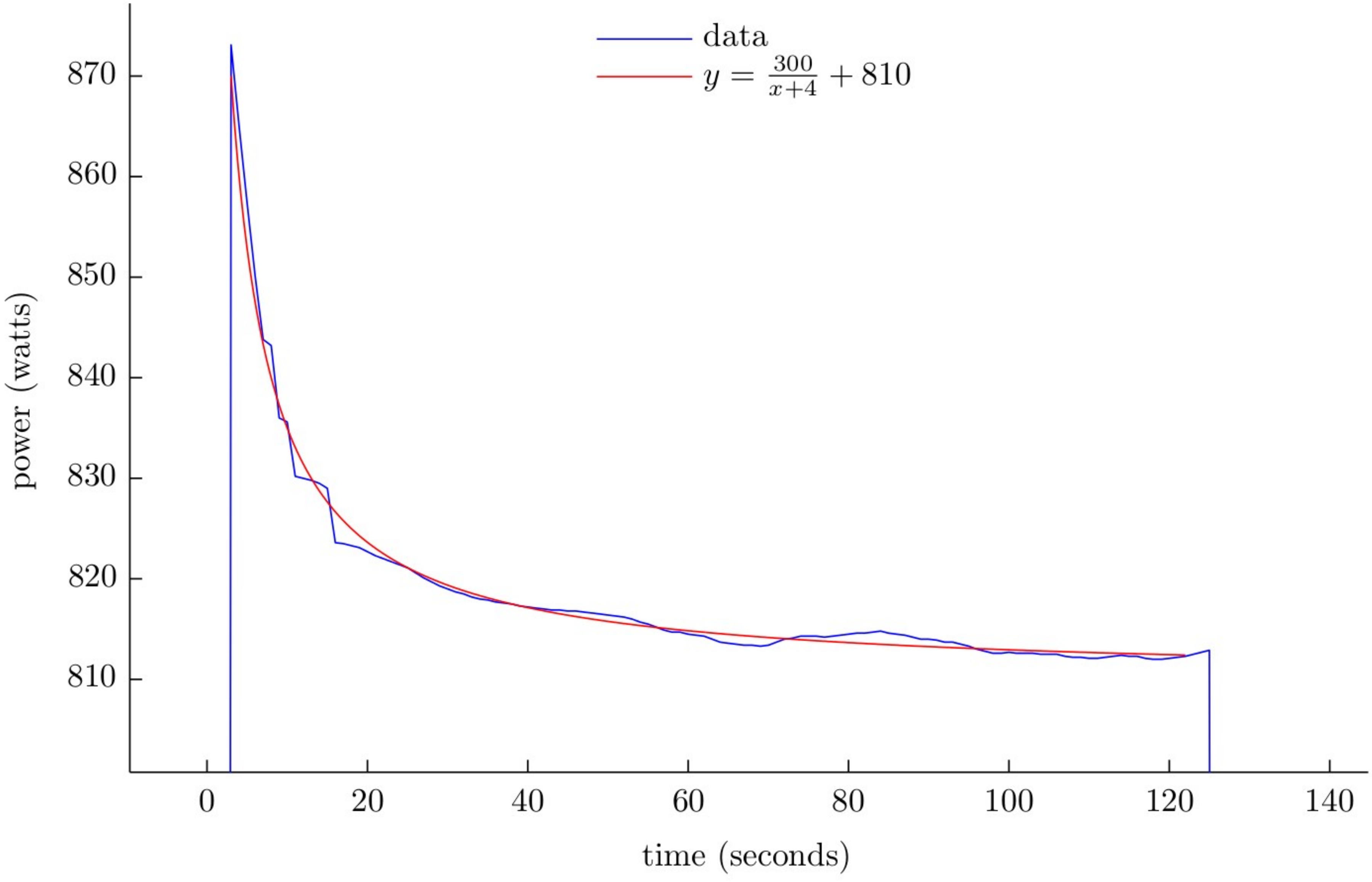
on constantly
repeat(on for 30s, off for 5s)
motor (fan)
power=240W
overshoot=?*
undershoot=?*
on constantly
motor (drum)
power=170W
overshoot=140W
undershoot=25W
repeat(on for 30s, off for 2s)
c)
heater
motor (fan)
motor (drum)
WARM UP (2000s)
on constantly
on constantly
repeat(30s, 2s)
STABILISE TEMP. (3000s)
repeat(30s, 5s)
on constantly
repeat(30s, 2s)
COOL
off
on
repeat
anticrease
off
off
repeat
off
0.1
0.7
0.9
0.7
0.2
0.1
0.3
1
1

Build a common library of component models

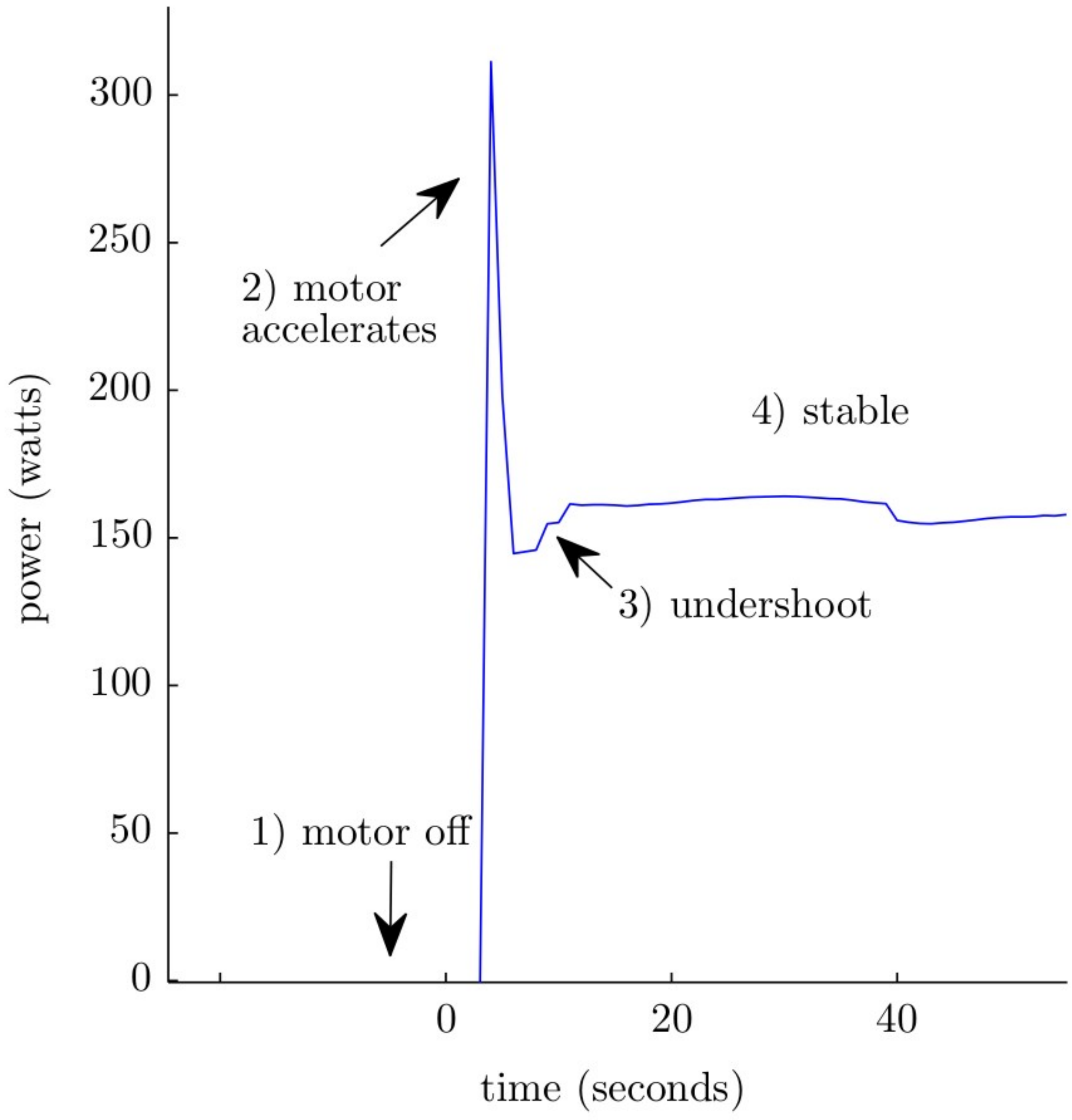
- heater
- motor
- compressor
- etc...

heater



data
$y = \frac{300}{x+4} + 810$
870
860
850
840
830
820
810
power (watts)
0
20
40
60
80
100
120
140
time (seconds)

motor



300
250
200
150
100
50
0
power (watts)
0
20
40
time (seconds)
2) motor
accelerates
4) stable
3) undershoot
1) motor off

References

•Darby. The effectiveness of feedback on energy consumption. A review for DEFRA of the literature on metering, billing and direct displays. (Environmental Change Institute, University of Oxford: 2006)

•Fischer. Feedback on household electricity consumption: a tool for saving energy? Energy Efficiency 1, 79–104 (2008).

•Hart. Nonintrusive appliance load monitoring. Proceedings of the IEEE 80, 1870–1891 (1992).

•Kim, Marwah, Arlitt, Lyon & Han. Unsupervised Disaggregation of Low Frequency Power Measurements. 11th International Conference on Data Mining 747–758 (2011)

•Kolter & Jaakkola. Approximate Inference in Additive Factorial HMMs with Application to Energy Disaggregation. Proceedings of the International Conference on Artifical Intelligence and Statistics (2012)

•Kolter & Johnson. REDD: A public data set for energy disaggregation research. SustKDD workshop (2011)

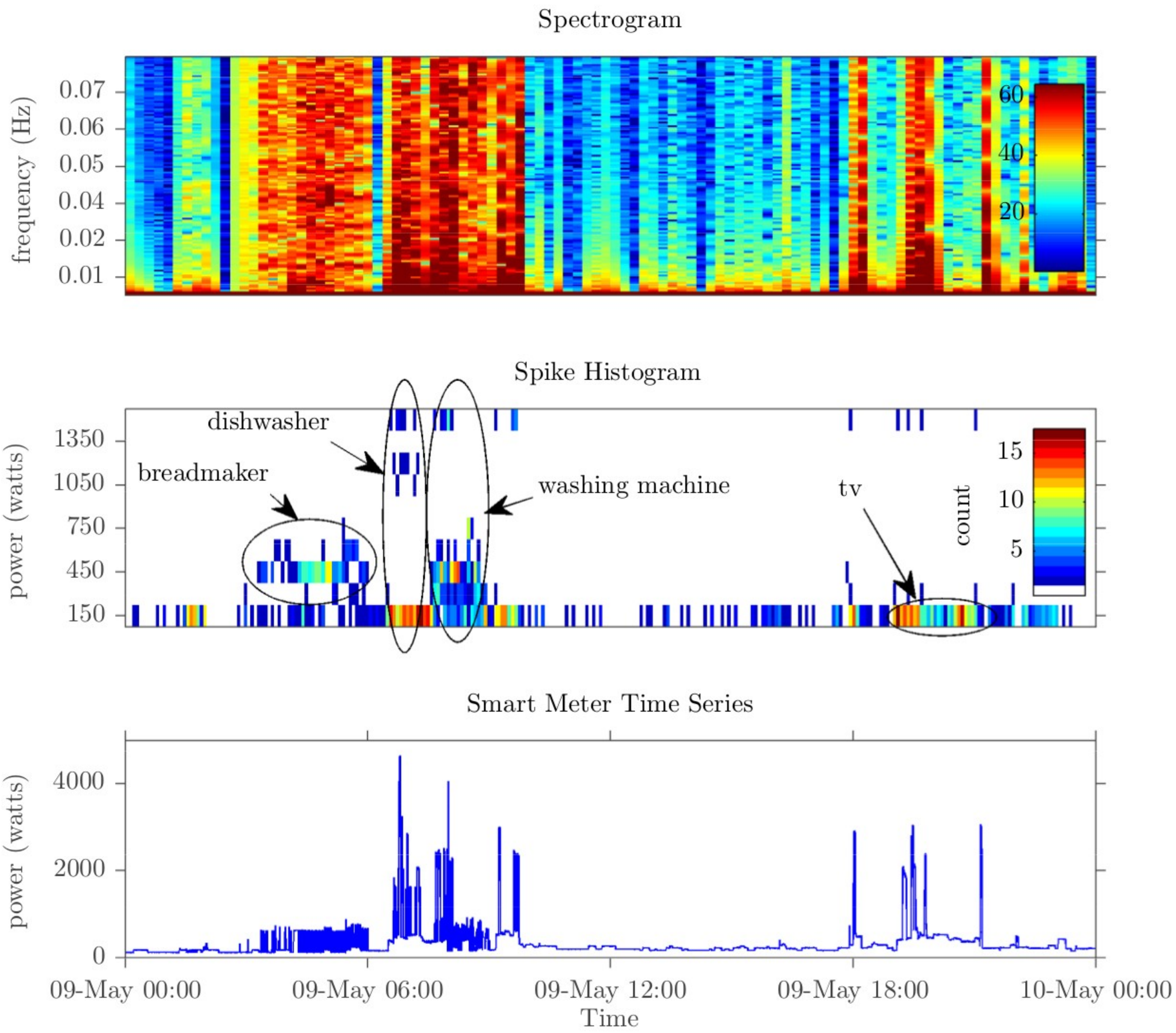
•Parson, Ghosh, Weal & Rogers. Non-intrusive Load Monitoring using Prior Models of General Appliance Types. in 26th AAAI Conference on Artificial Intelligence (2012)

•Seryak & Kissock. Occupancy and Behavioral Affects on Residential Energy Use. American Solar Energy Society, Solar conference 717–722 (2003)

•Socolow. The twin rivers program on energy conservation in housing: Highlights and conclusions. Energy and Buildings 1, 207–242 (1978).

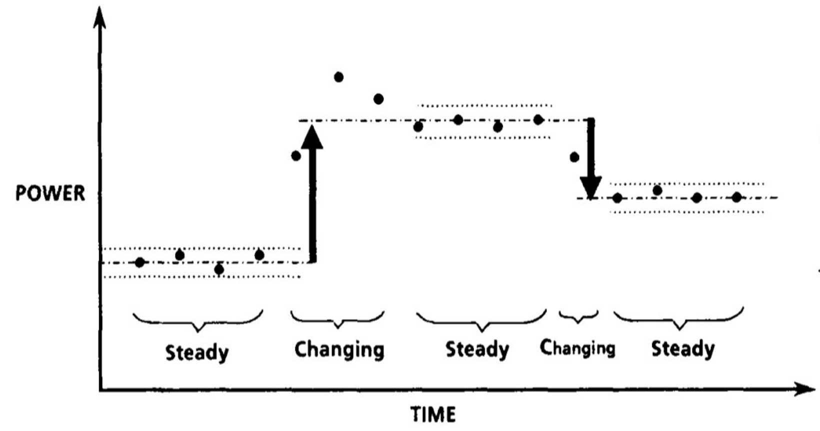
•Winett & Neale. Psychological framework for energy conservation in buildings: Strategies, outcomes, directions. Energy and Buildings 2, 101–116 (1979).

Frequency-domain features



Limitations to Hart's approach

- Only uses steady-state features



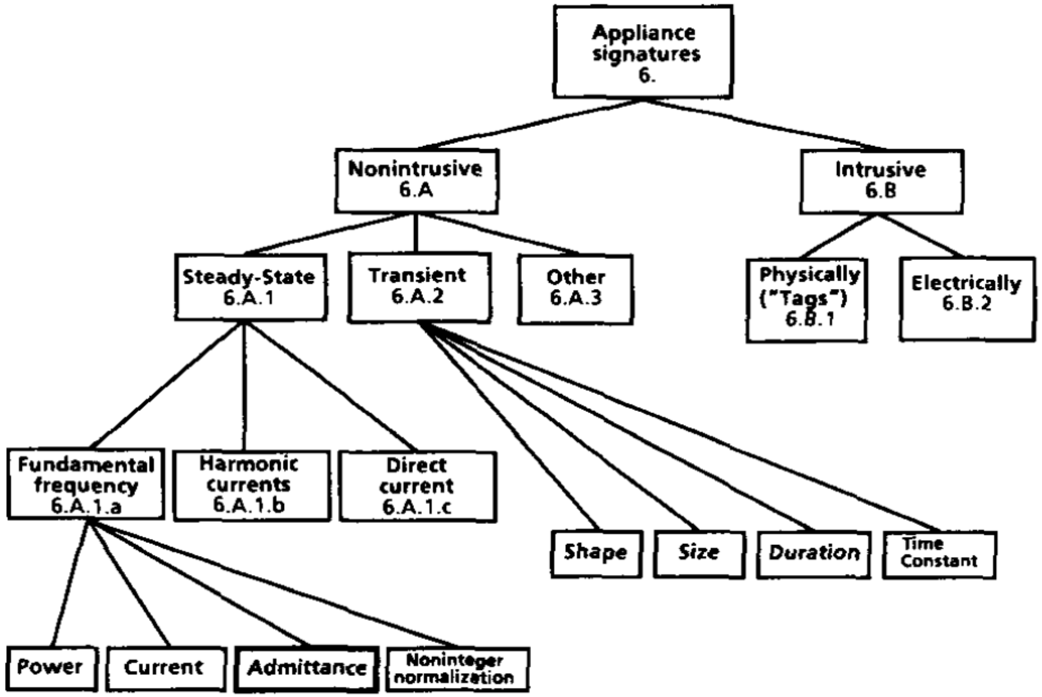


Fig. 5. Signature Taxonomy. Out of many possible informative signatures, our prototypes have relied only on admittance.

Limitations to Hart's approach

- Only uses steady-state features
- Requires measurements of real power and reactive power at 1Hz
  - Home energy monitors only measure apparent power at 0.2 Hz
  - Utility-installed smart meters likely to measure real & reactive power at 0.2 Hz

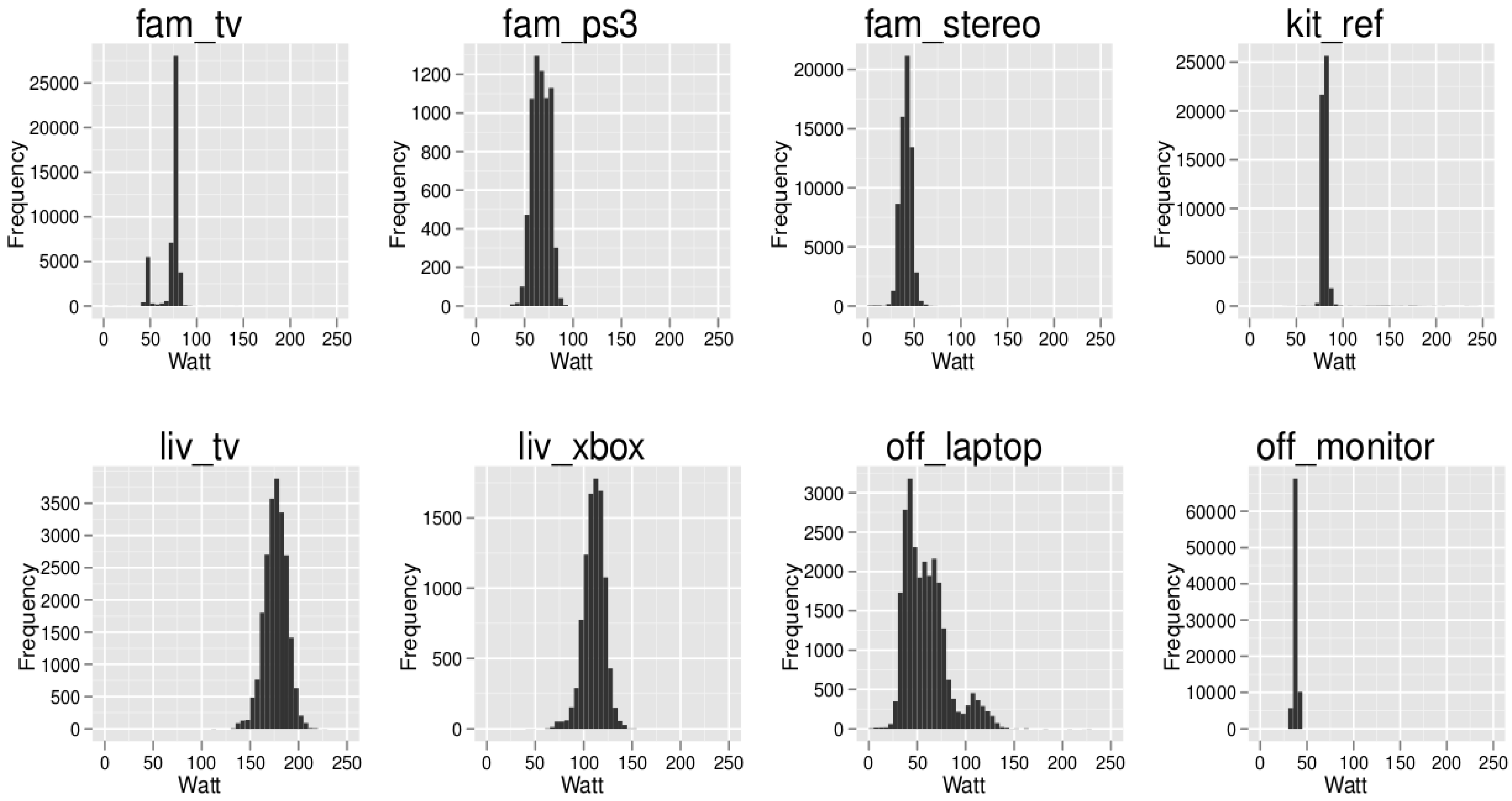
- Deliberately ignores appliances with power consumption <150W (most modern appliances use <150W)
- Cannot deal with continually variable devices (like dimmable lights)
- Many modern appliances have similar power factors
- Struggles with multi-state appliances

Kim *et al* 2011

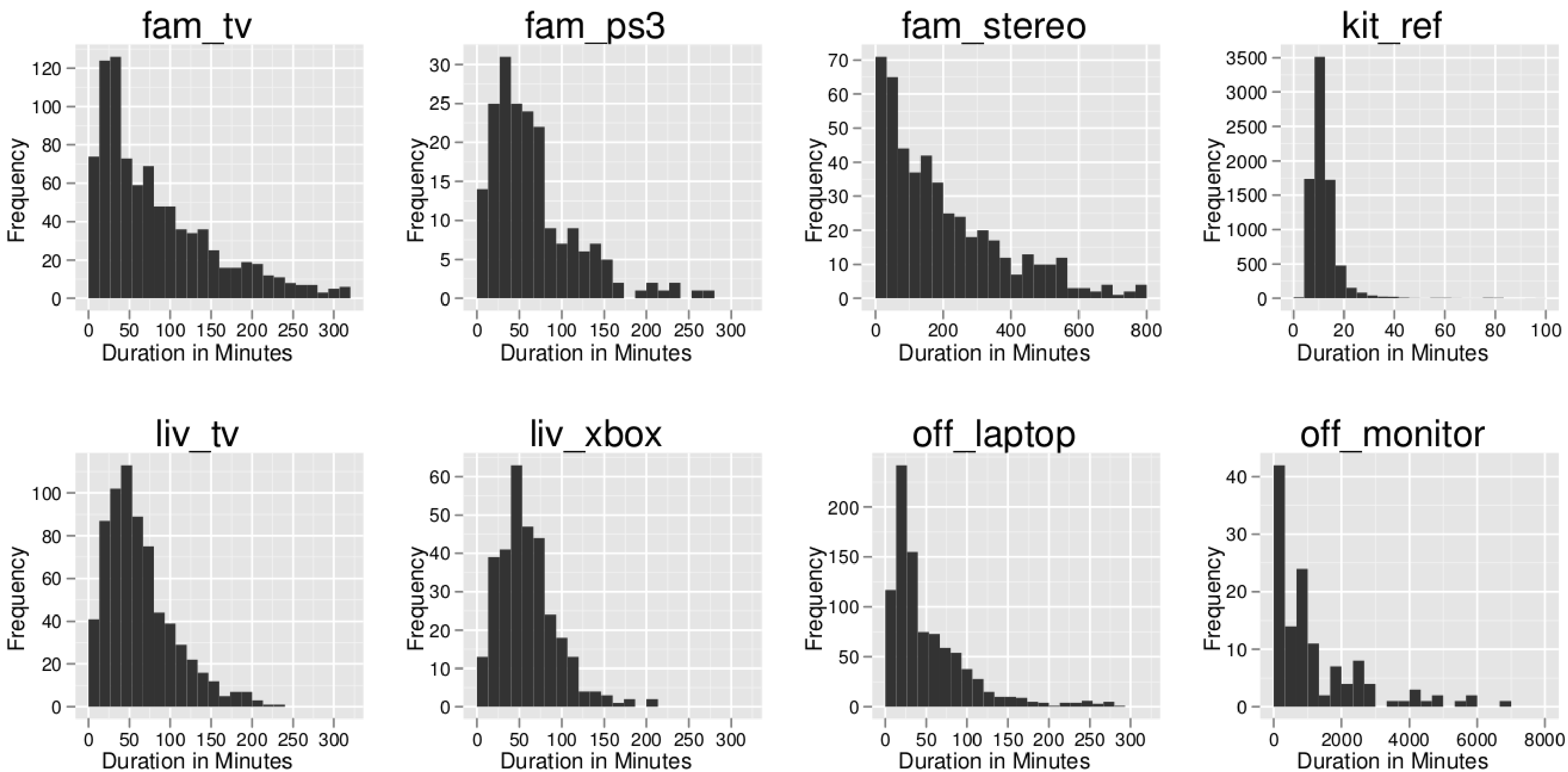
- Unsupervised learning from the smart meter data
- Uses low-frequency smart meter data
- Used an extended HMM (a CFHMM)
- Papers starts by exploring smart meter data

H. Kim, M. Marwah, M. F. Arlitt, G. Lyon, and J. Han, ‘Unsupervised Disaggregation of Low Frequency Power Measurements’, in 11th International Conference on Data Mining, Arizona, 2011, pp. 747-758.

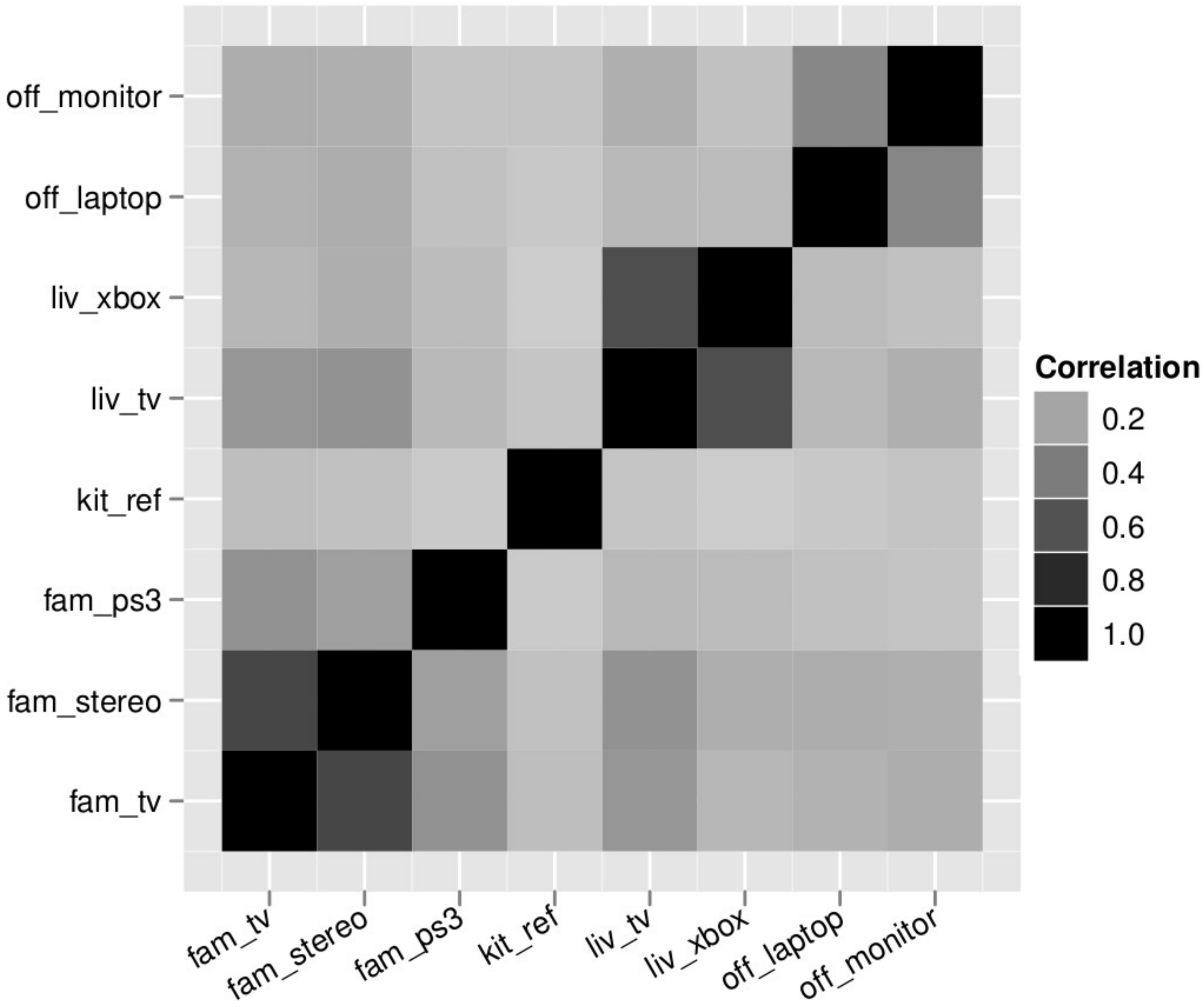
Kim et al: Histograms of appliance power consumption



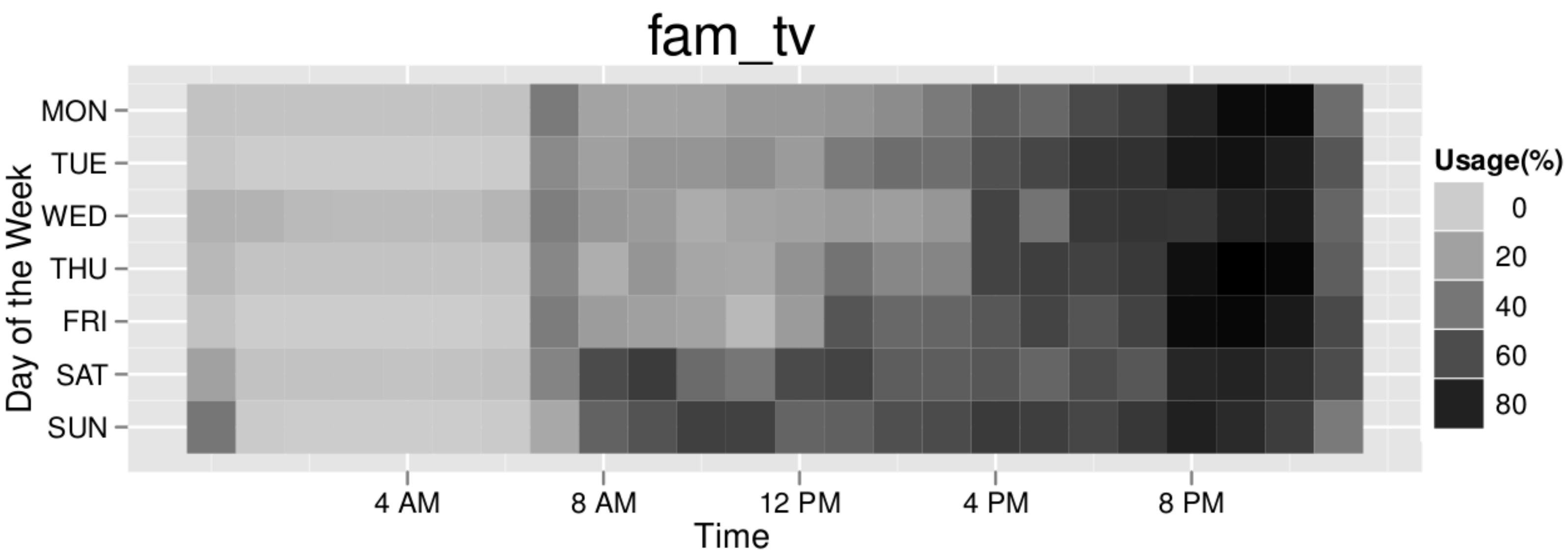
Kim et al: Histograms of appliance on- durations

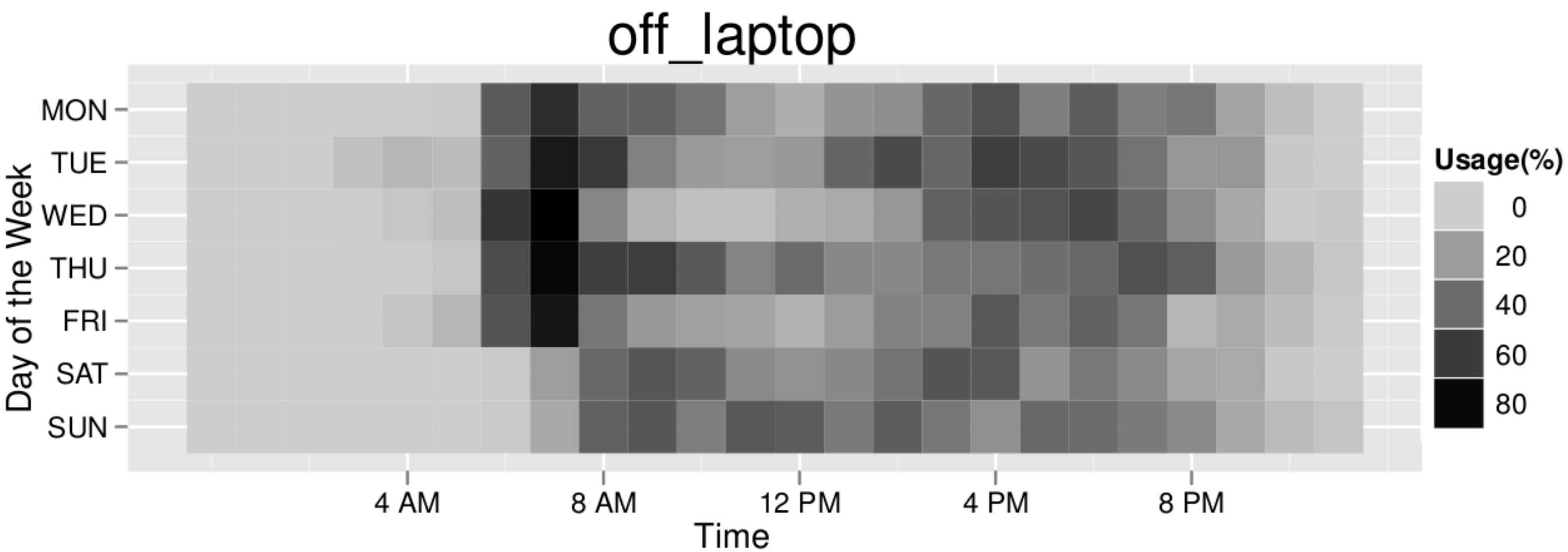


Kim et al: Correlations between appliances



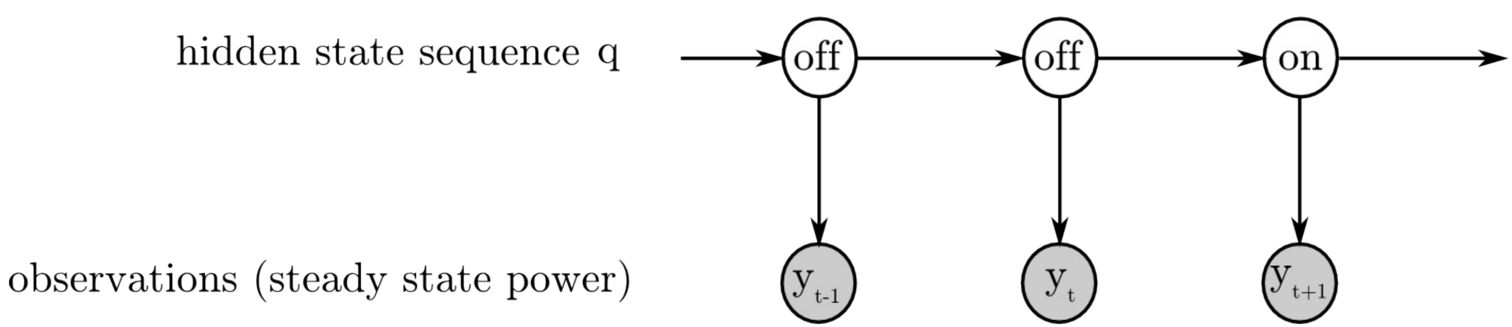
Kim et al: Time of day





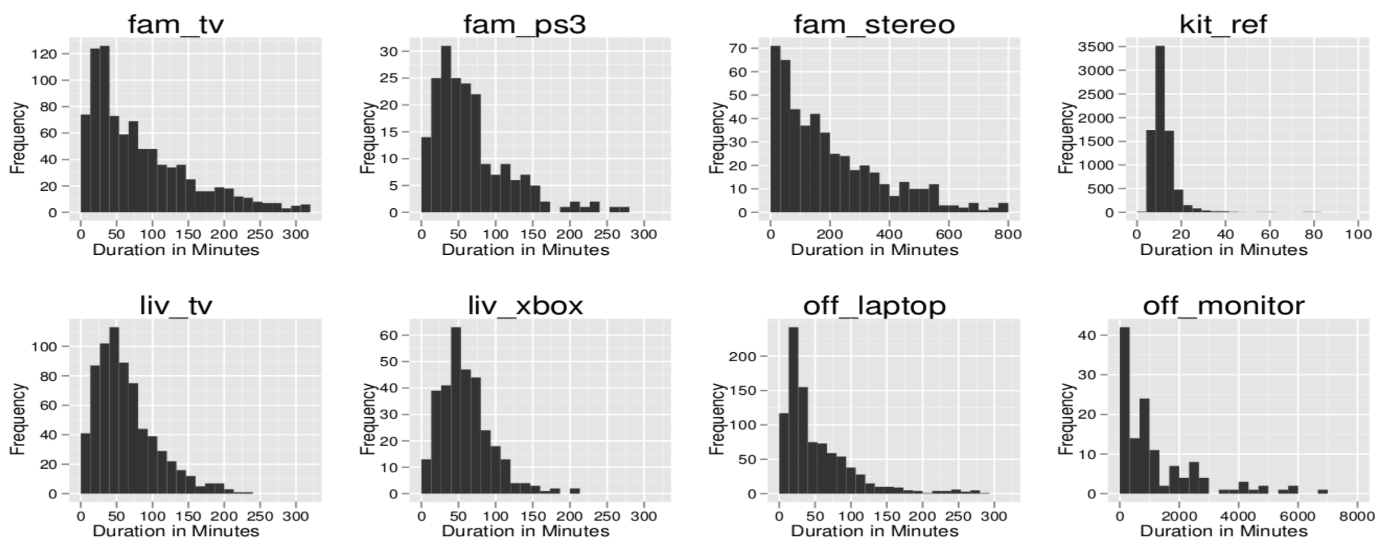
Hidden Markov Model

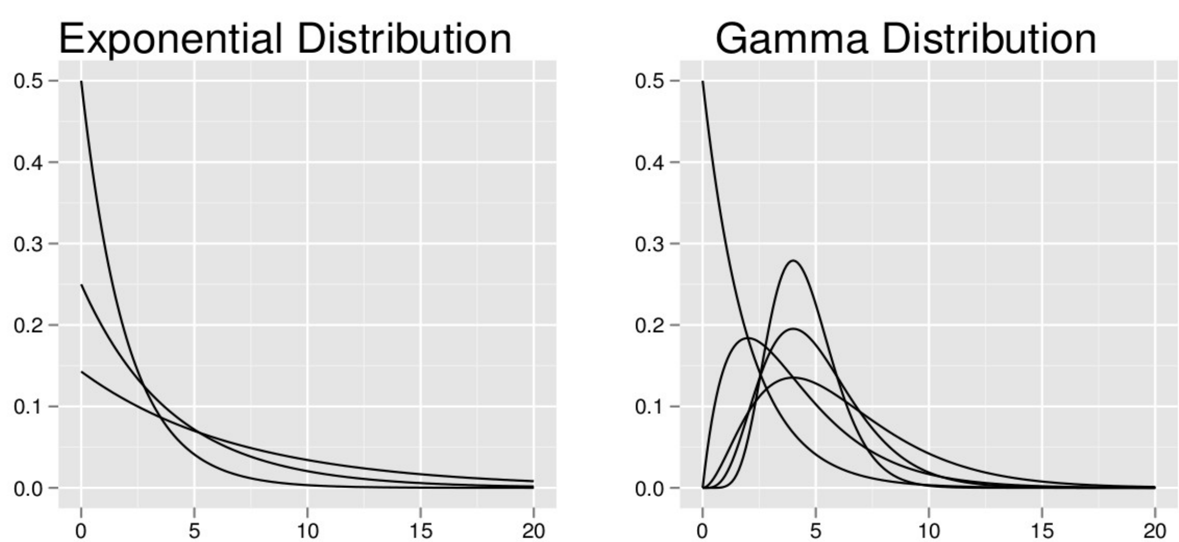
discrete time HMM



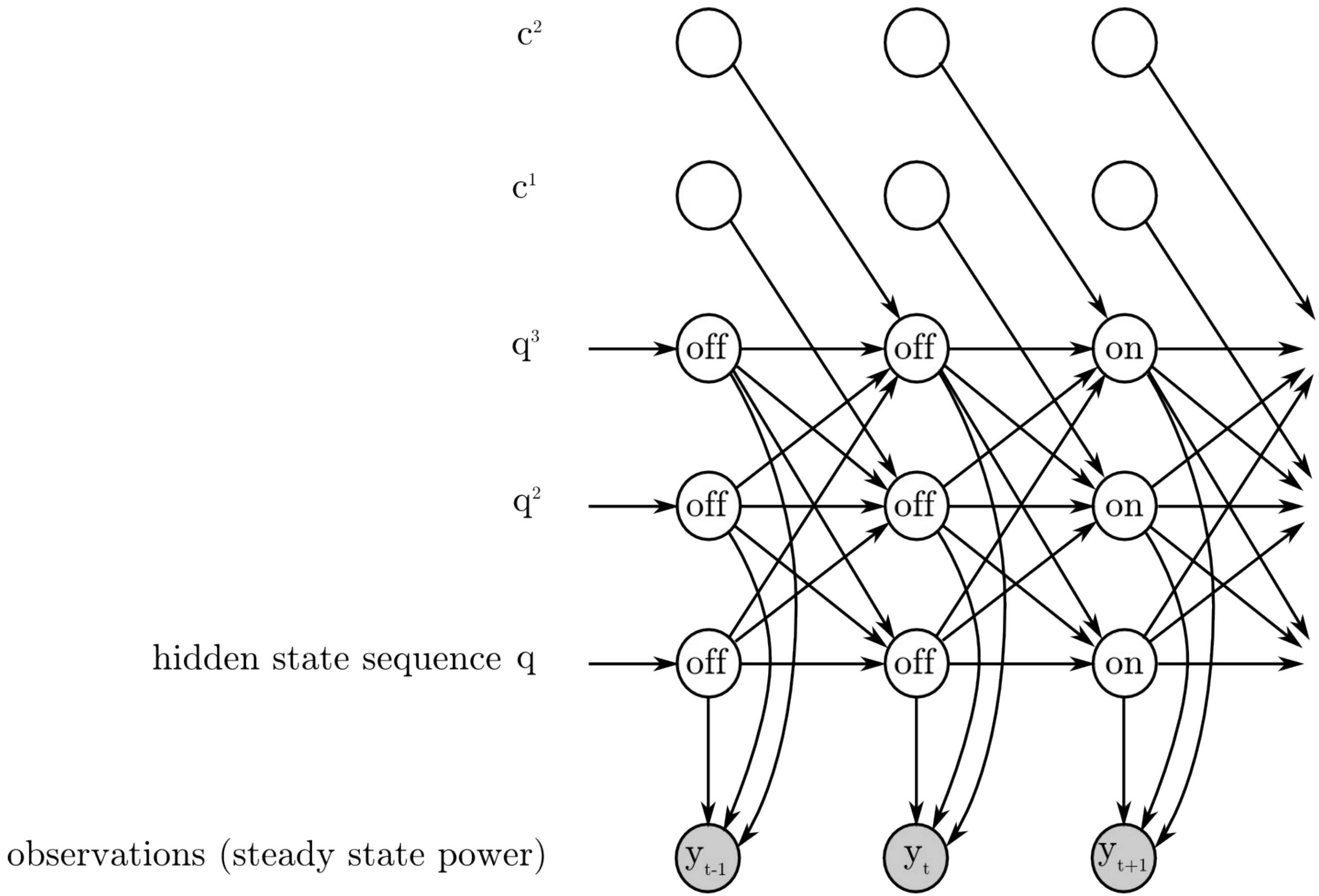
Hidden Semi-Markov Model

HMMs model state occupancy using a geometric distribution.
But on-durations are better modelled by a gamma distribution.





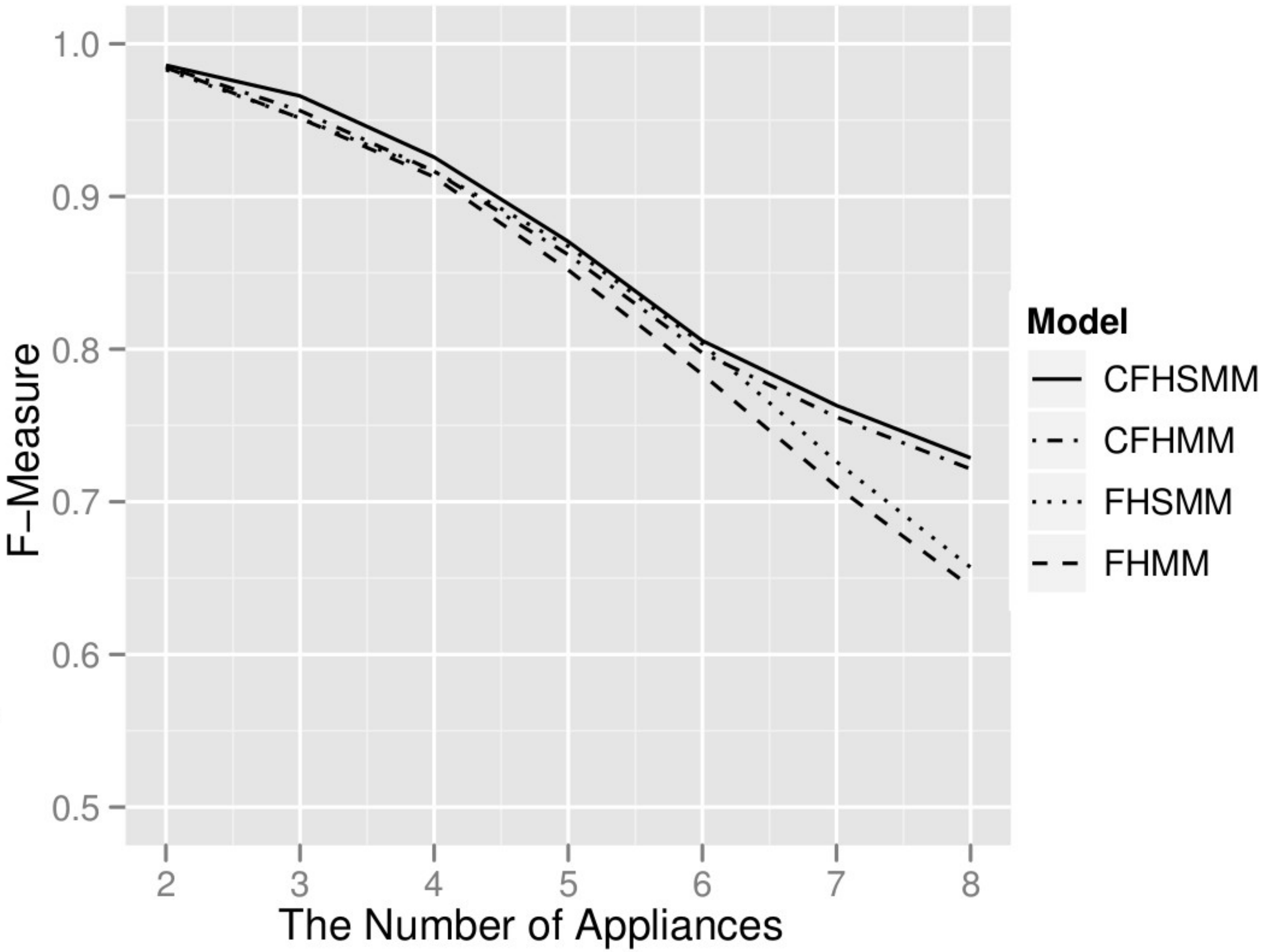
Conditional Factorial HSMM



Kim et al

- Parameters estimated using an Expectation Maximisation algorithm.
- Gibbs sampling is used as the E-step
- Hidden states estimated using simulated annealing

Kim et al: Results



Precision is defined as $\frac{TP}{TP+FP}$ and *Recall* is defined as $\frac{TP}{TP+FN}$. Thus,

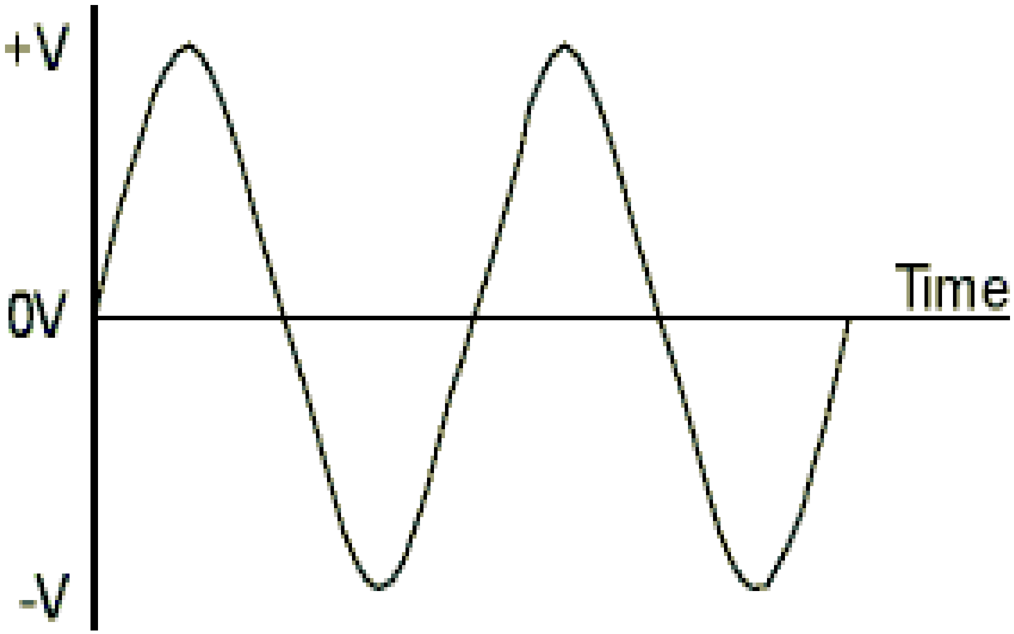
$$F\text{-}measure = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

Kim et al: Limitations

- Requires explicit knowledge of # of appliances
- Does not attempt to model multi-state appliances: "*our results revealed that the tested methods work well for appliances with simple or modestly complex power signatures, but less well for more complex signatures*"
- Only uses steady-state
- Are HMMs appropriate for modelling appliances?

Real power does useful work

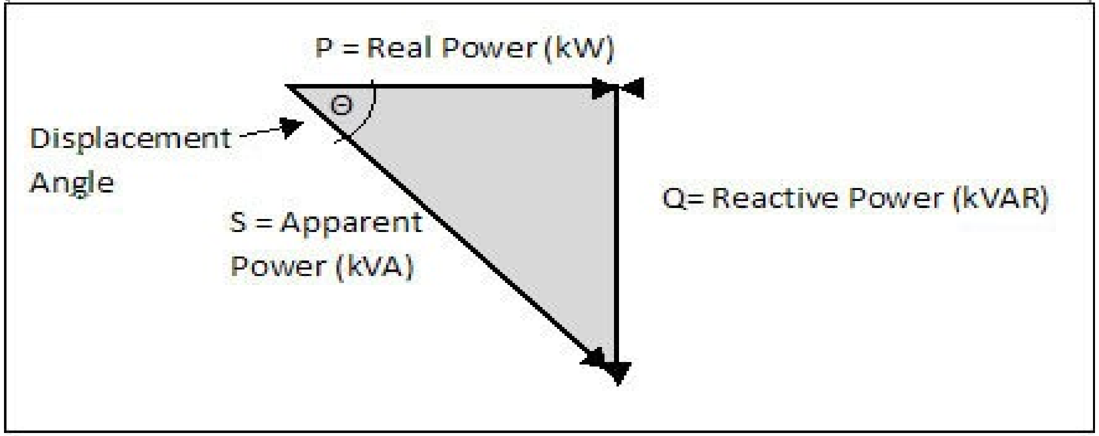
Consider powering a resistive load with an AC power source:



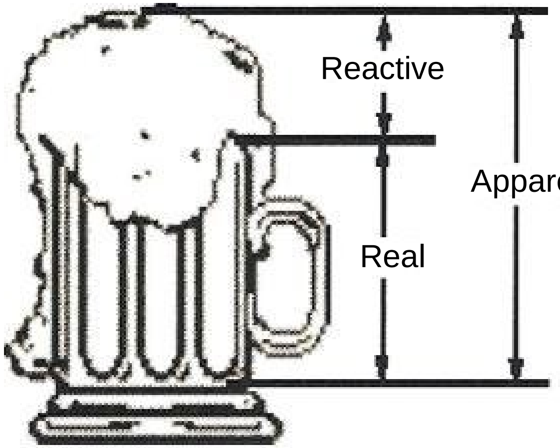
• Voltage and current are in phase
• Power factor = 100% (all power delivered by power source is used to do useful work)

Reactive power just heats the distribution wiring

Powering an inductive load with an AC power source



$$power\ factor = \frac{real}{apparent}$$



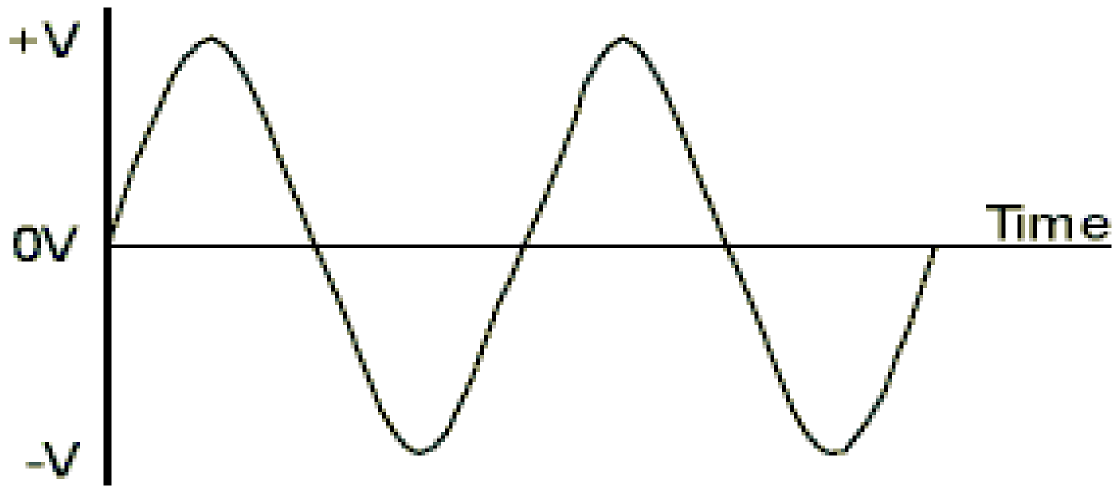
Existing approaches: comparing performance

- Impossible to meaningfully compare published performance
  - labs use their own datasets
  - different appliances
  - labs use different performance metrics
  - no code is published

- A group at MIT released “The Reference Energy Disaggregation Data Set” (REDD) in 2011 consisting of meter data from 6 different homes. http://redd.csail.mit.edu/

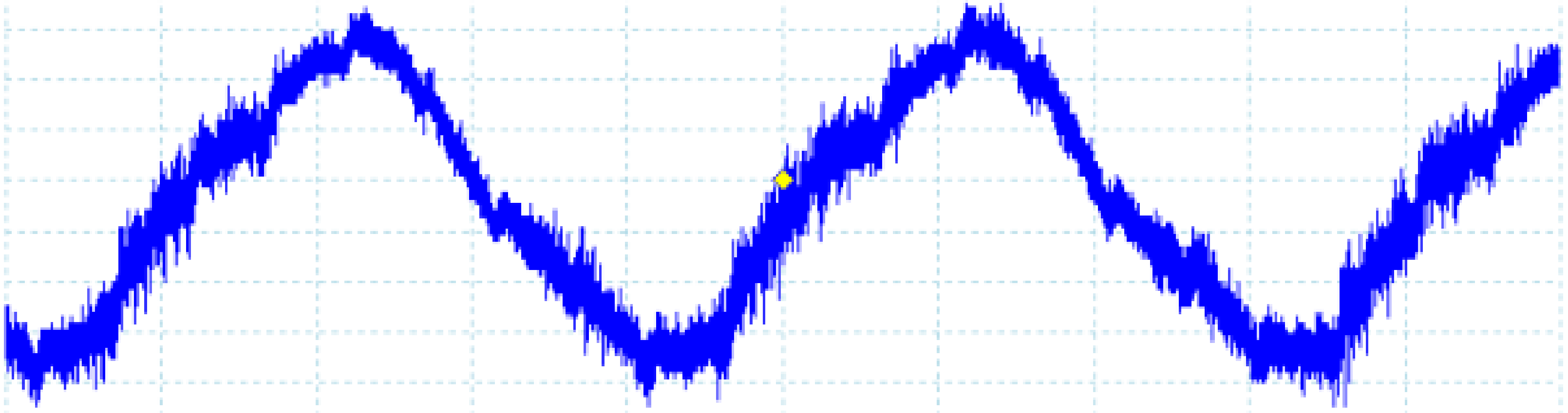
Most research uses high frequency sampling

The mains AC waveform is **not** a nice, clean sine wave like this:

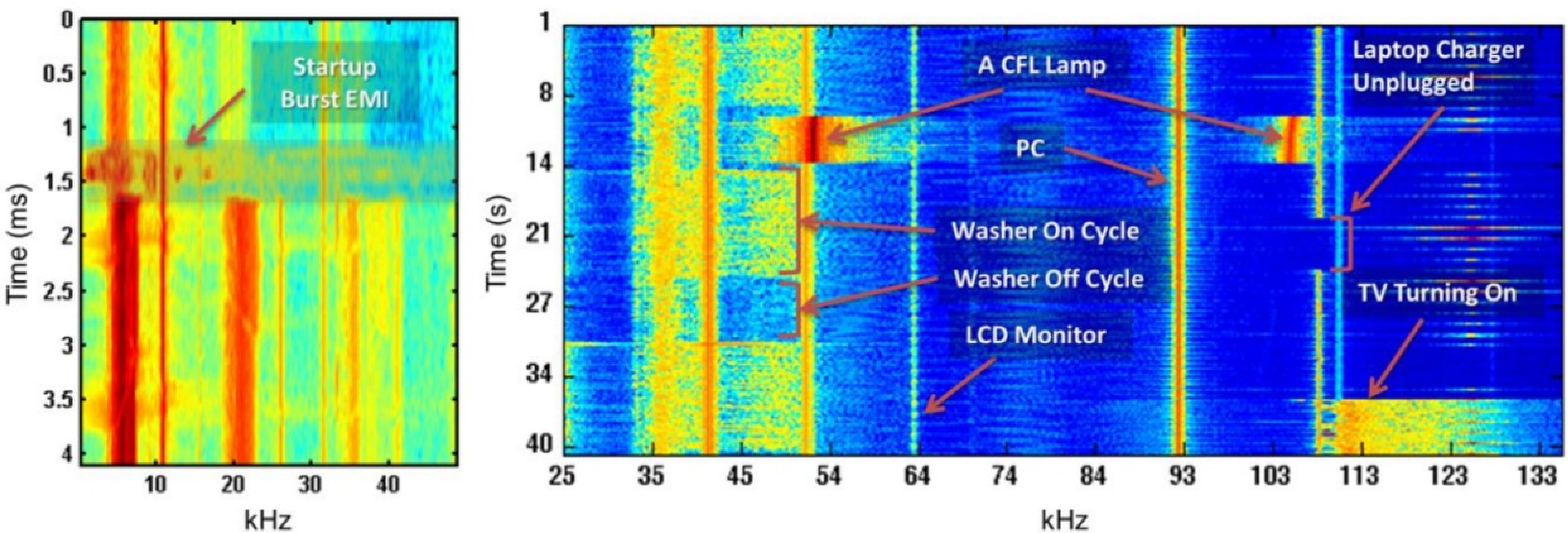


Most research uses high frequency sampling

instead it looks more like this:



Most research uses high frequency sampling



Few researchers have focussed on approaches which work with smart meters and home energy monitors which sample about once every five seconds

NAVETAS
Energy Management

Interactive House Demo

The interactive house demonstrates how the unique appliance monitoring technology works in the home and the real time information that can be provided to consumers.

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Online Monitoring

- Products Overview
- Product Matrix
  - > Smart Hub
  - > Energy Monitor
  - > In-Home LCD Display
  - > Smart Gas Index
  - > Online Monitoring
  - > Mobile Apps

Online Monitoring

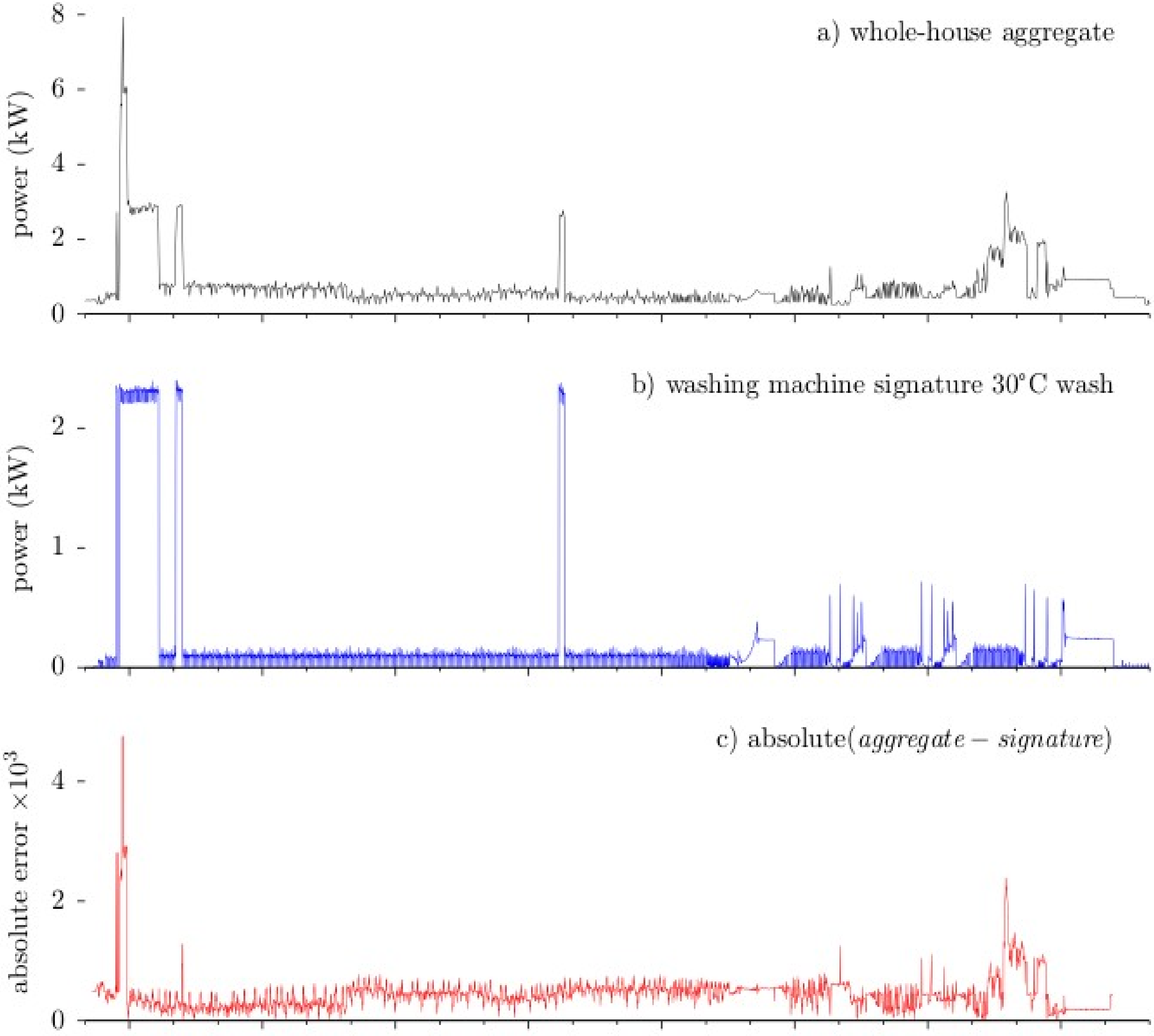
Overview | Contact Details

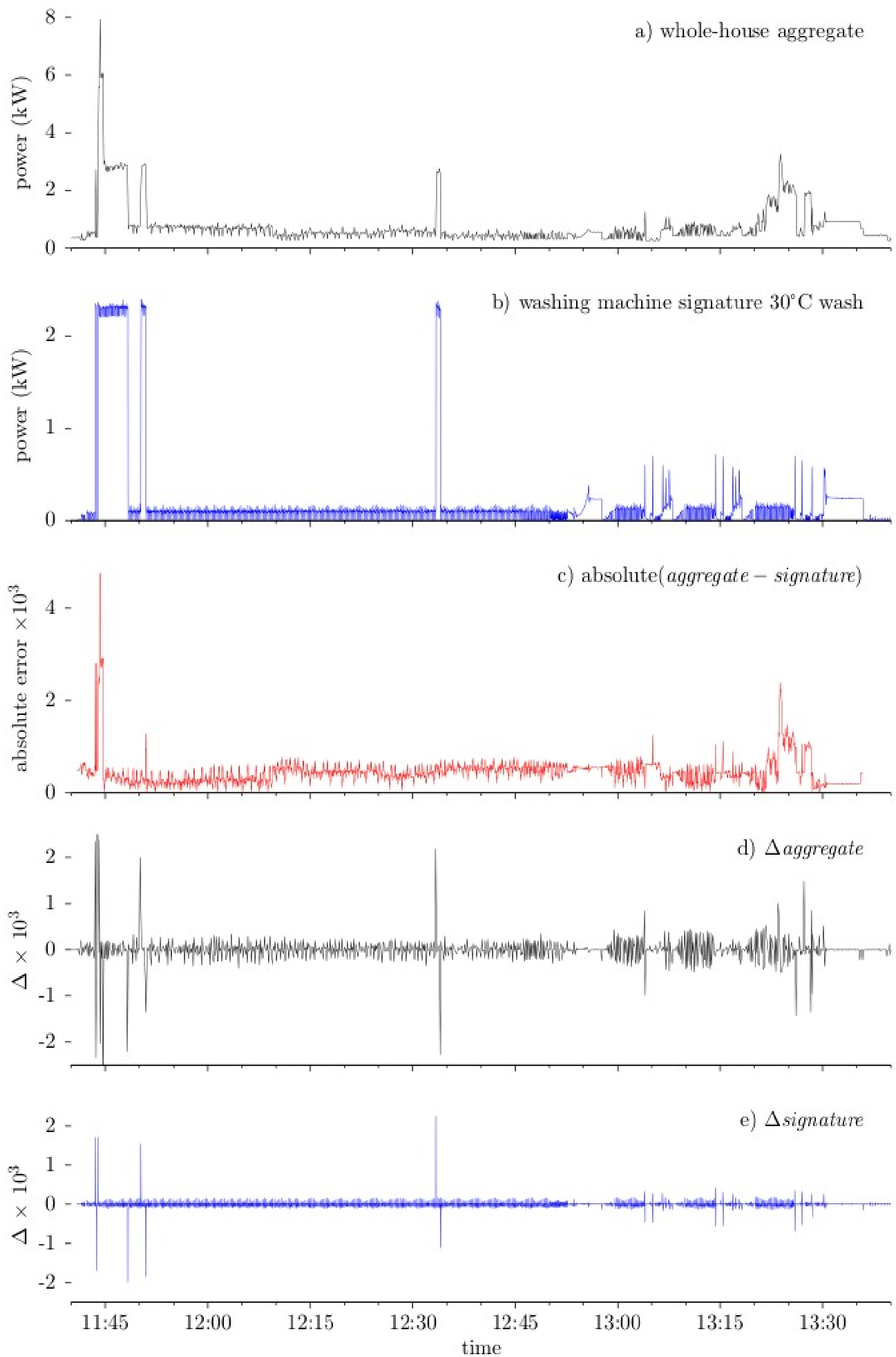
In a world where there are long term expectations of rising energy costs and increasing consumer awareness of climate change and the environmental impact of CO2 emissions, our web based applications focus on translating energy consumption KWh register data into meaningful user friendly information.

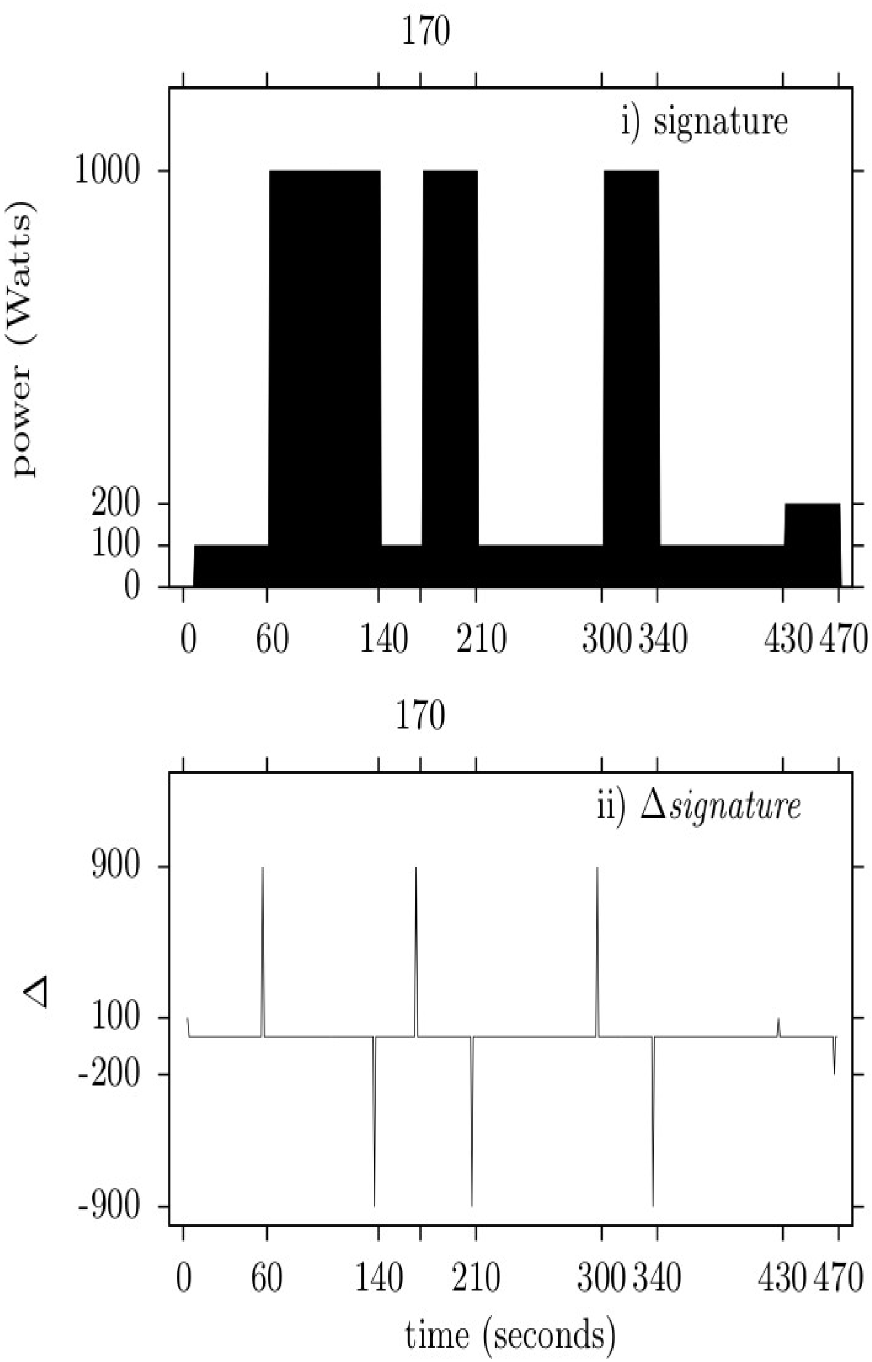
Navetas are able to provide web based applications including electronic billing, electronic bill checking, historical energy consumption data, profile information, energy efficiency health check and usage by appliance. Our unique appliance monitoring application, Powered by ISE, empowers consumers to analyse their consumption habits and energy consumption choices.

Through providing easily accessible historical information online, consumers will be able to for the first time validate their overall energy bill online, see their bill broken down by appliance (itemised) much like a mobile phone bill, and understand their consumption profiles for particular days, weeks and months. So if for example a household hosted a children's party, the consumer will be able to see exactly how much energy that was used for the party.

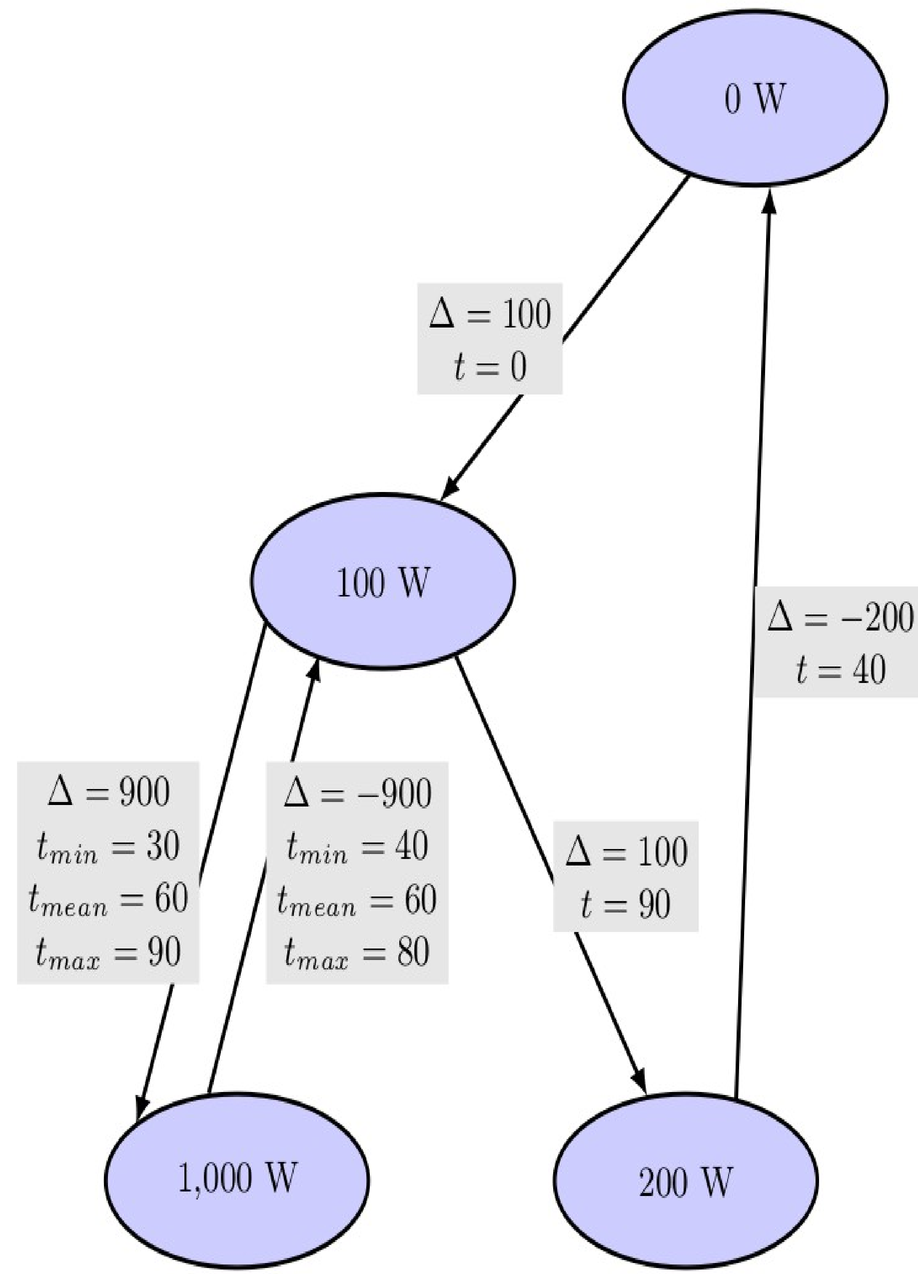
Enlarge


a) whole-house aggregate
power (kW)
0
2
4
6
8
b) washing machine signature 30°C wash
power (kW)
0
1
2
c) absolute(aggregate − signature)
absolute error ×10^3
0
2
4

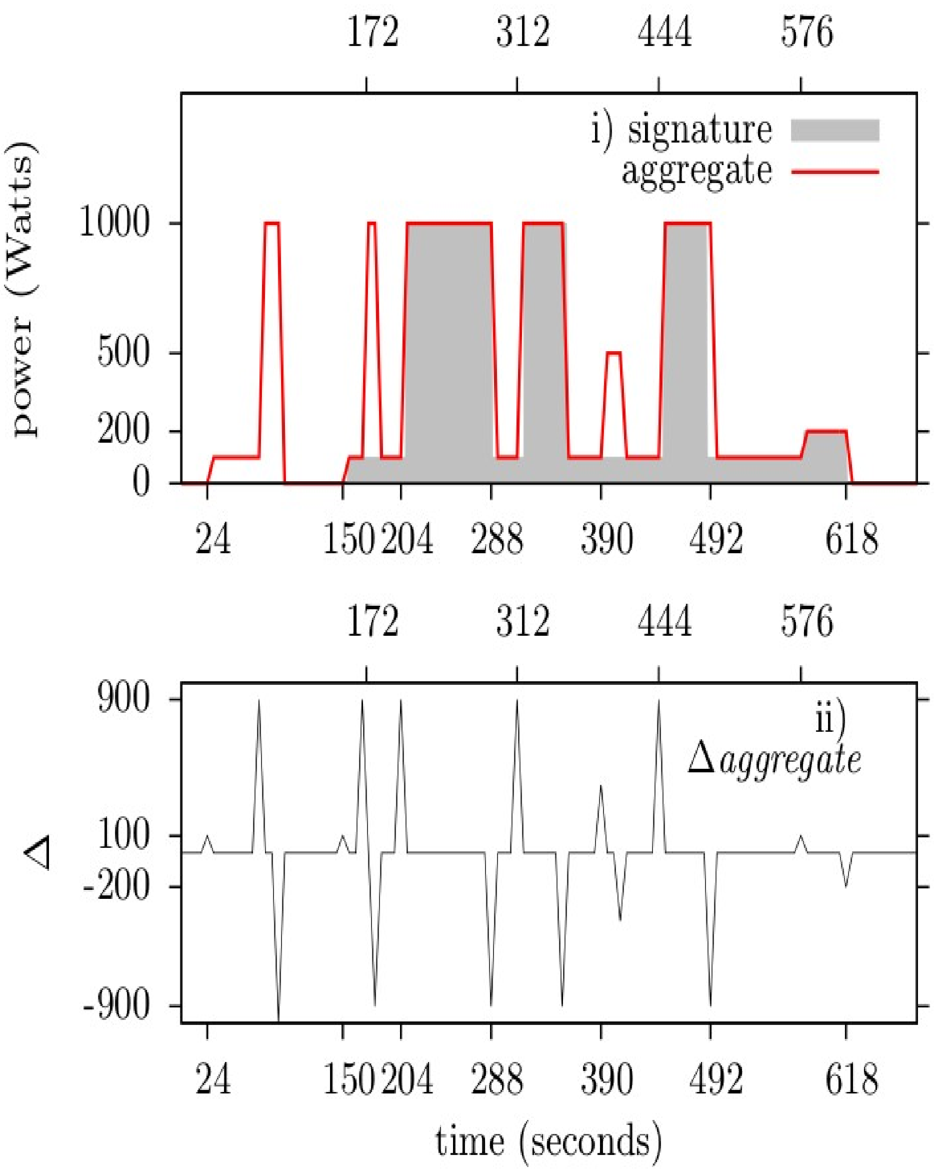

a) whole-house aggregate
power (kW)
b) washing machine signature 30°C wash
power (kW)
c) absolute(aggregate − signature)
absolute error ×10^3
d) Δaggregate
Δ × 10^3
e) Δsignature
Δ × 10^3
11:45
12:00
12:15
12:30
12:45
13:00
13:15
13:30
time


170
i) signature
power (Watts)
1000
200
100
0
0 60 140 210 300 340 430 470
170
ii) Δsignature
900
100
-200
-900
Δ
0 60 140 210 300 340 430 470
time (seconds)

(a)

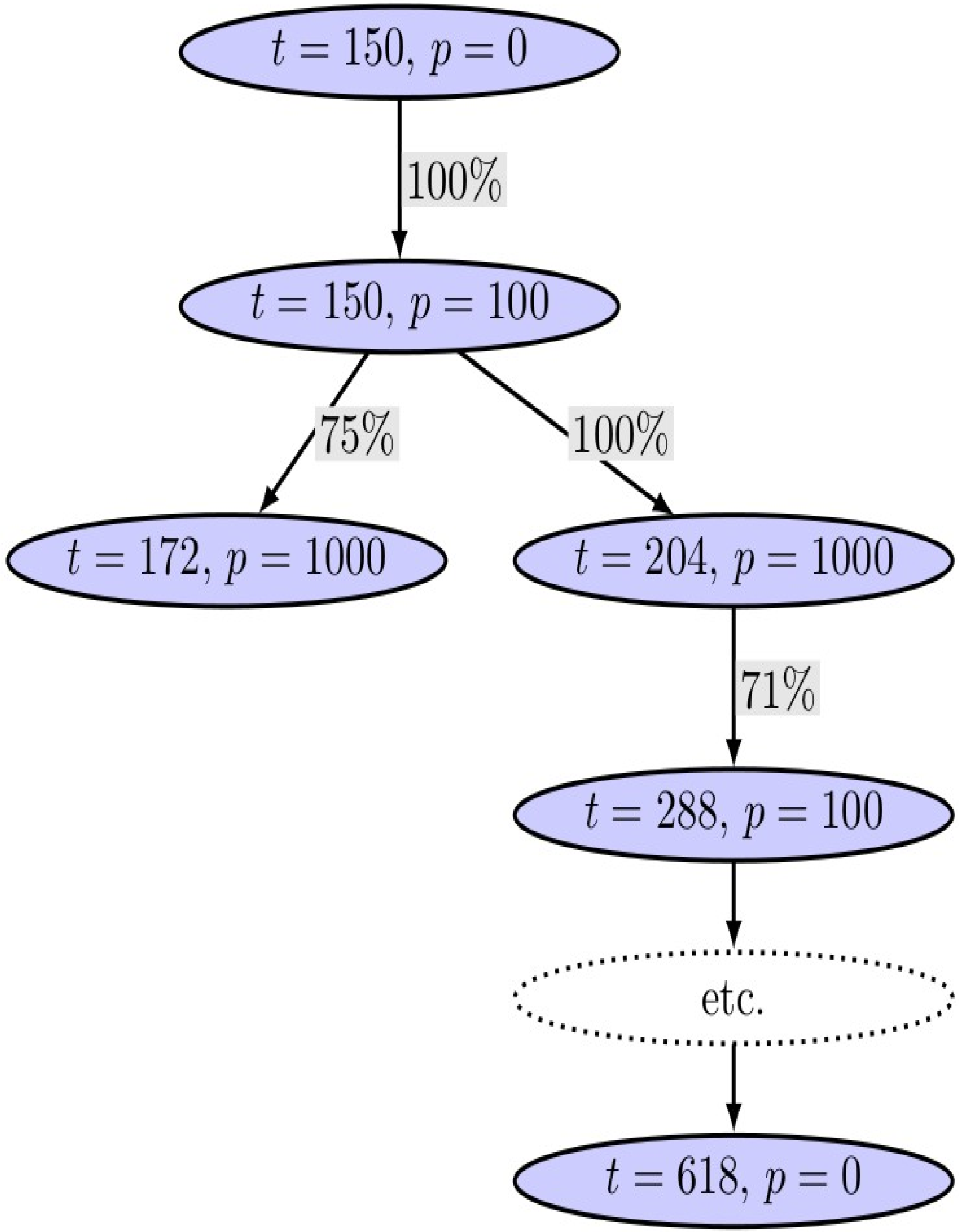

0 W
Δ = 100
t = 0
100 W
Δ = −200
t = 40
Δ = 900
t_min = 30
t_mean = 60
t_max = 90
Δ = −900
t_min = 40
t_mean = 60
t_max = 80
Δ = 100
t = 90
1,000 W
200 W

(b)



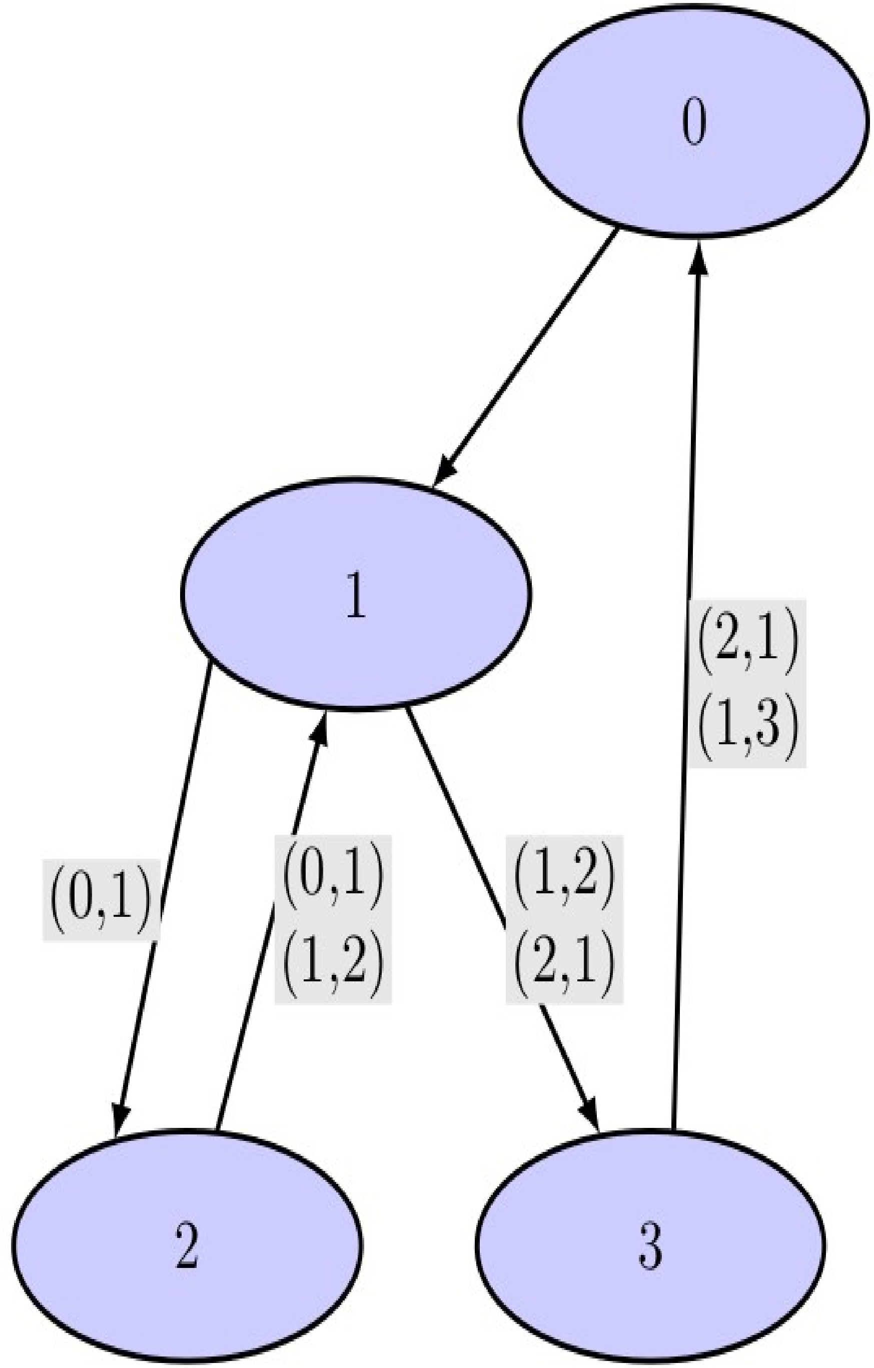
172
312
444
576
i) signature
aggregate
power (Watts)
1000
500
200
0
24
150
204
288
390
492
618
ii)
$\Delta aggregate$
900
100
-200
-900
Δ
time (seconds)

(a)

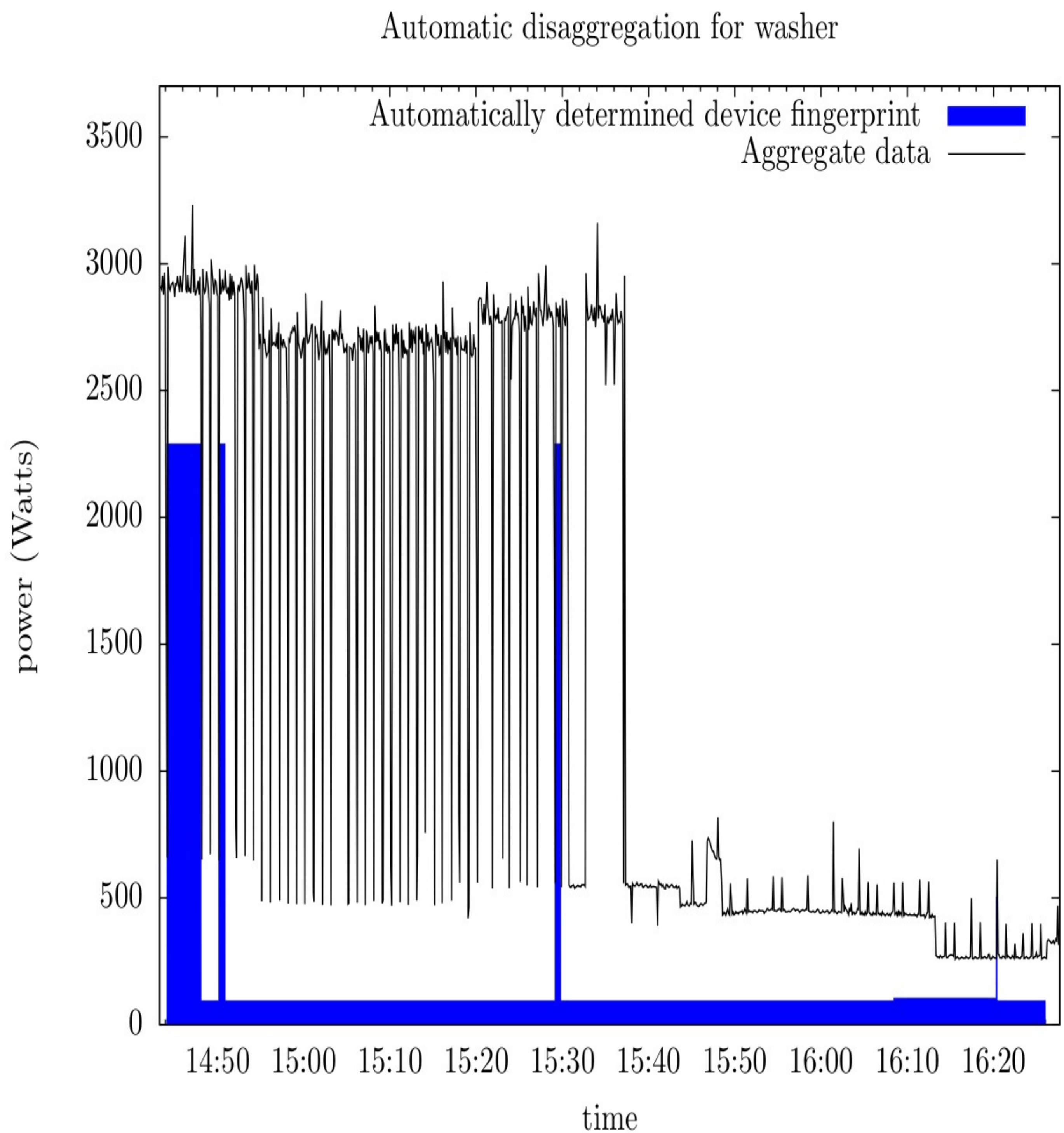


$t = 150,\ p = 0$
100%
$t = 150,\ p = 100$
75%
100%
$t = 172,\ p = 1000$
$t = 204,\ p = 1000$
71%
$t = 288,\ p = 100$
etc.
$t = 618,\ p = 0$

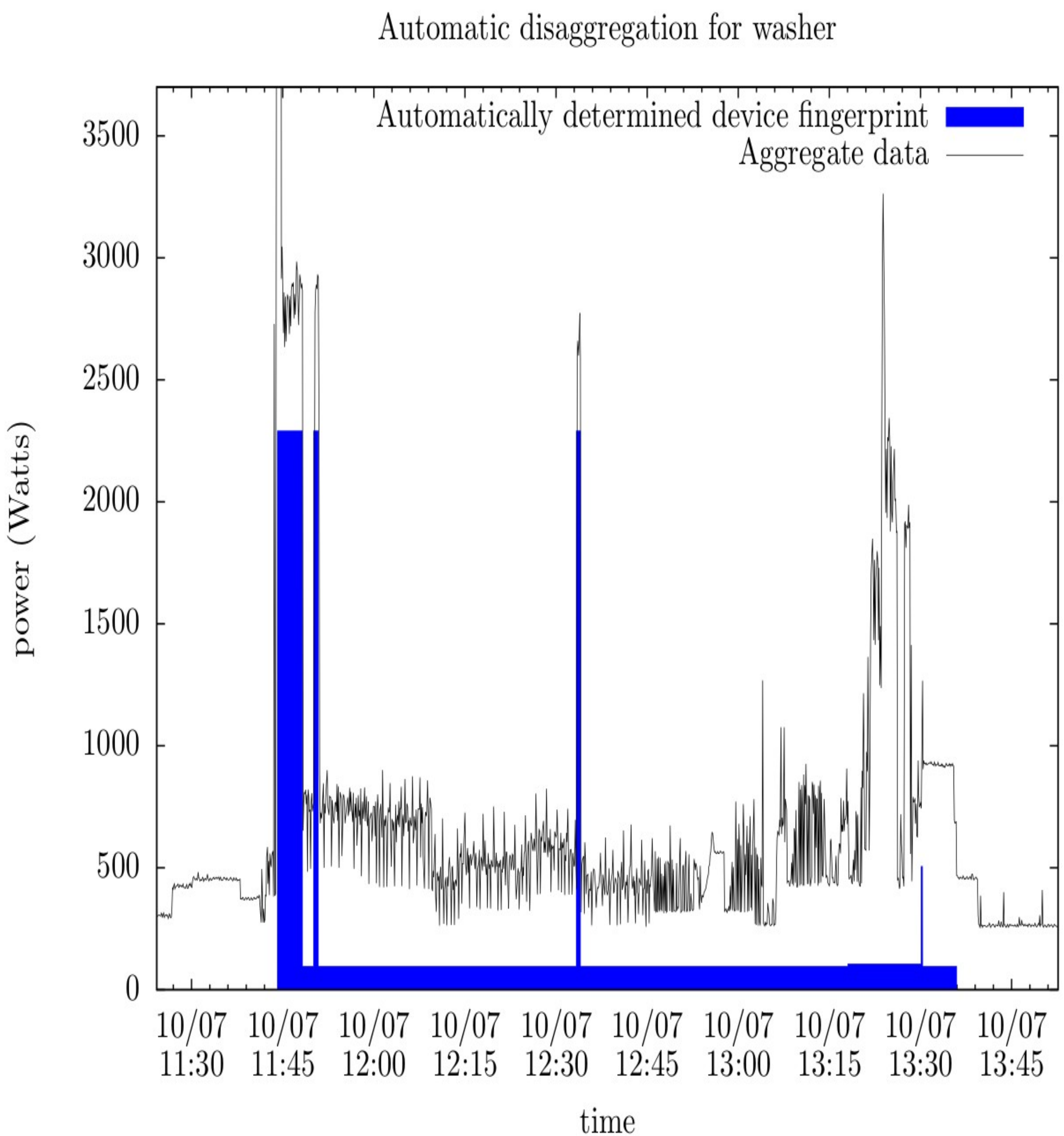
(b)



0
1
2
3
(0,1)
(0,1)
(1,2)
(1,2)
(2,1)
(2,1)
(1,3)

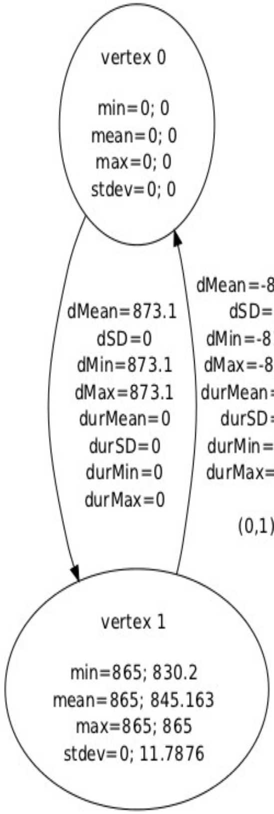


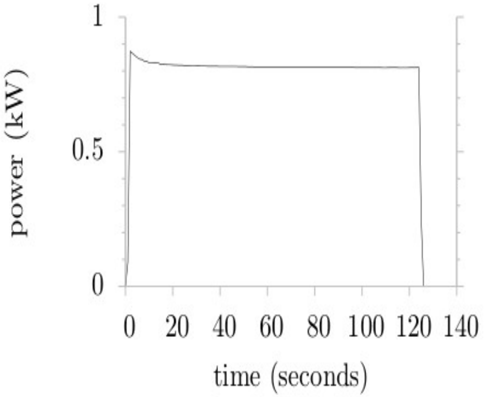
Automatic disaggregation for washer
Automatically determined device fingerprint
Aggregate data
power (Watts)
time
0
500
1000
1500
2000
2500
3000
3500
14:50
15:00
15:10
15:20
15:30
15:40
15:50
16:00
16:10
16:20



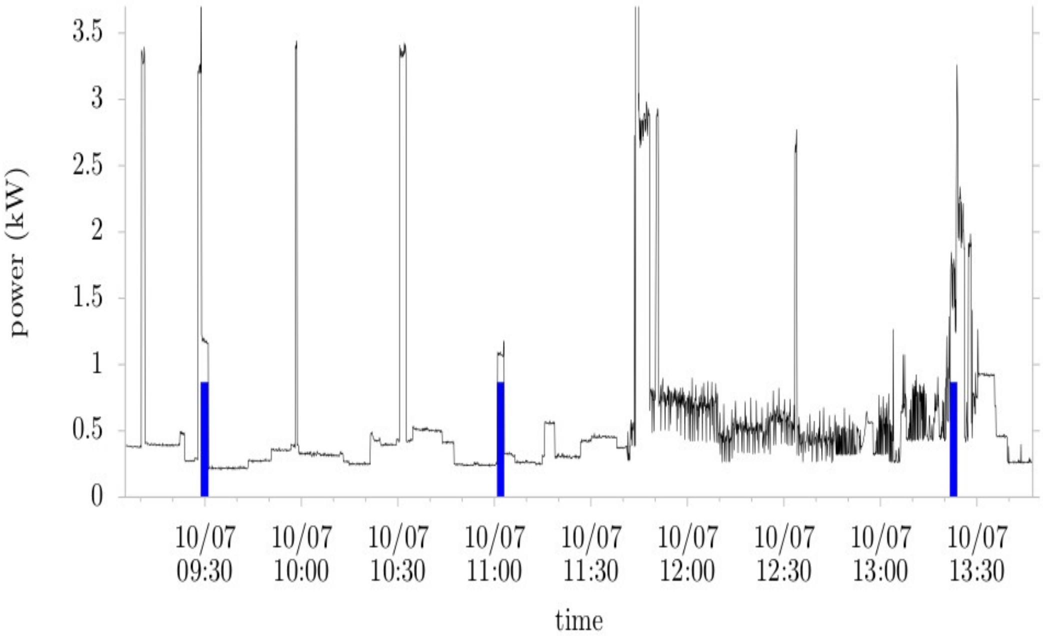
Automatic disaggregation for washer
Automatically determined device fingerprint
Aggregate data
power (Watts)
3500
3000
2500
2000
1500
1000
500
0
10/07 11:30
10/07 11:45
10/07 12:00
10/07 12:15
10/07 12:30
10/07 12:45
10/07 13:00
10/07 13:15
10/07 13:30
10/07 13:45
time

Toaster

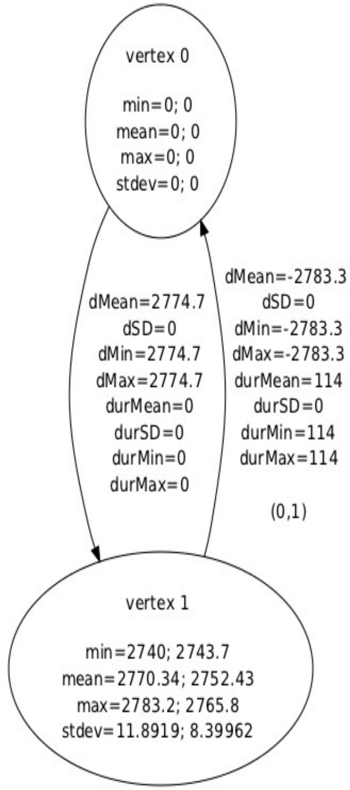


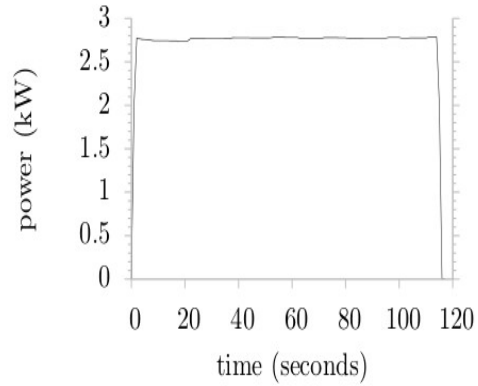


Time	Av likelihood	Correct?
9:28:46	0.30	Y
11:00:57	0.91	Y
13:21:40	0.59	Y

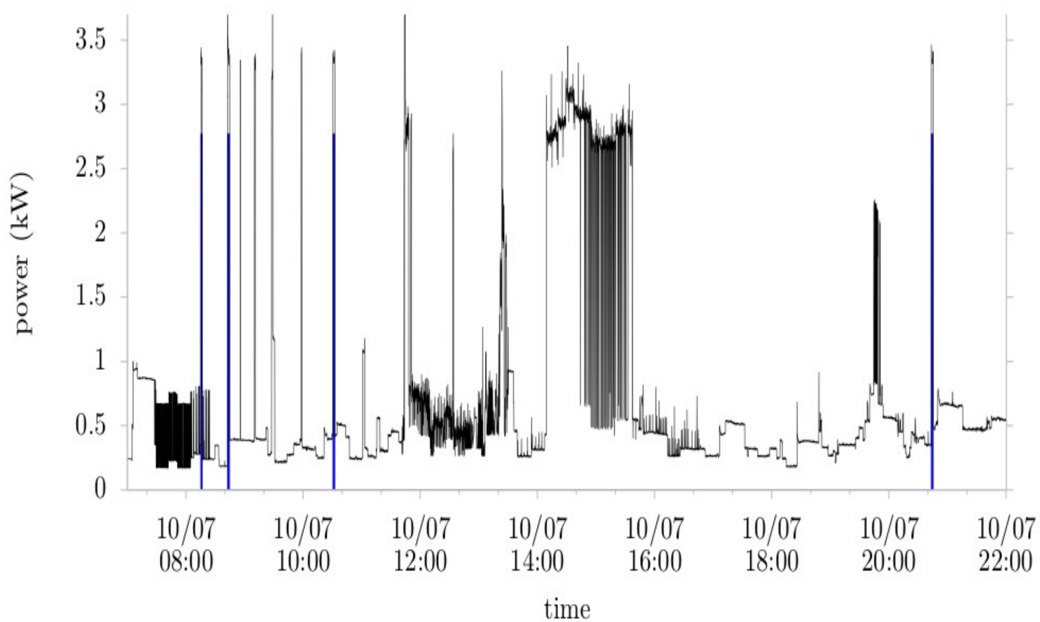


Kettle (1 signature)

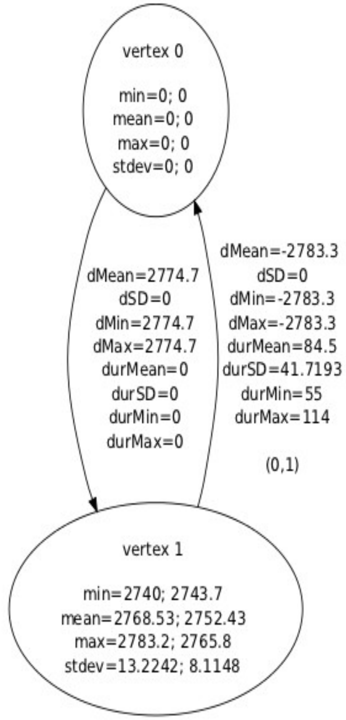


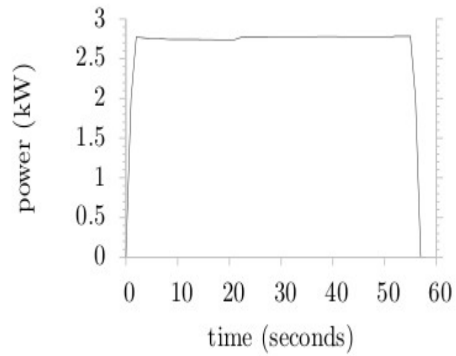


Time	Av likelihood	Correct?
08:15:08	0.72	Y
08:42:23	0.59	Y
08:55:38	—	false neg
09:10:12	—	false neg
09:27:48	—	false neg
09:58:04	—	false neg
10:30:32	0.88	Y
20:43:35	0.87	Y
22:08:21	—	false neg

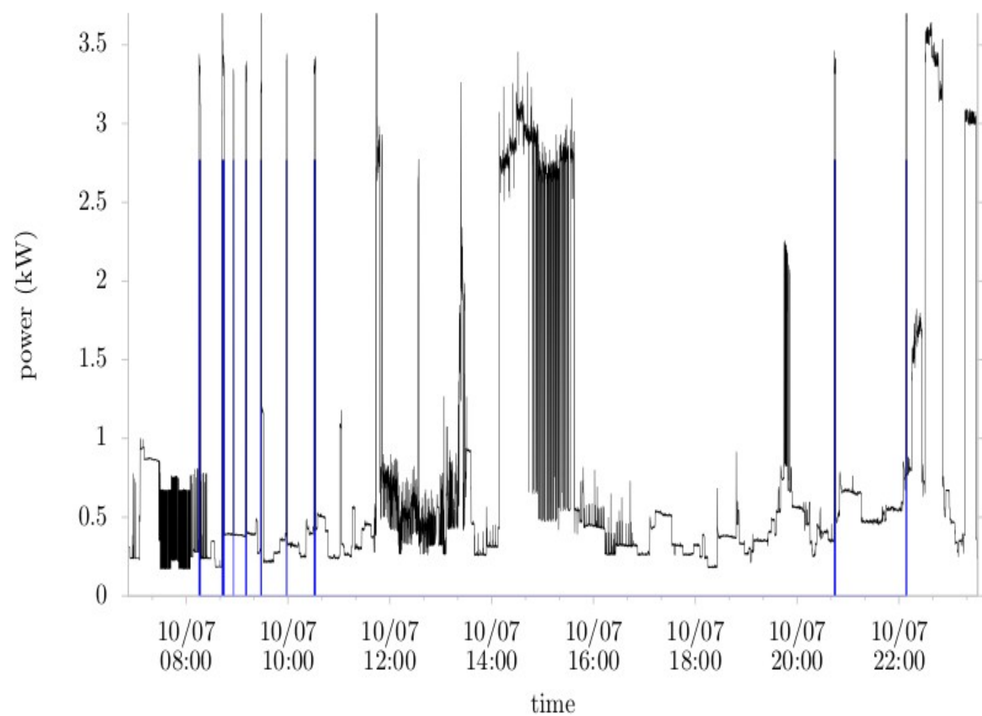


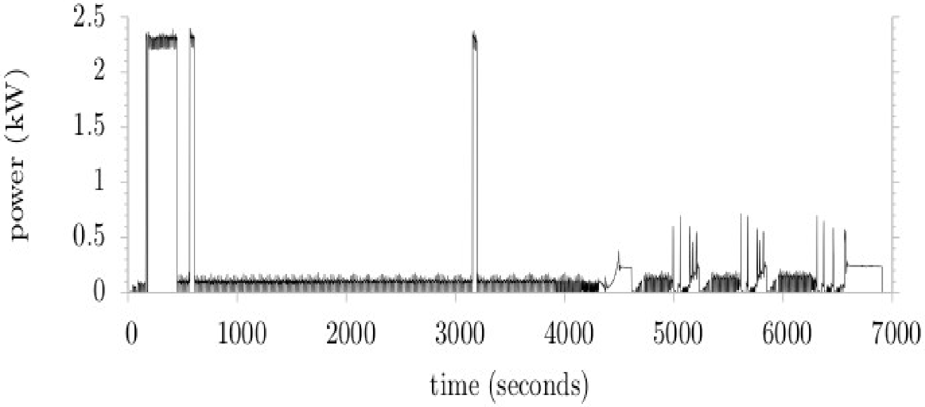
Kettle (2 signatures)



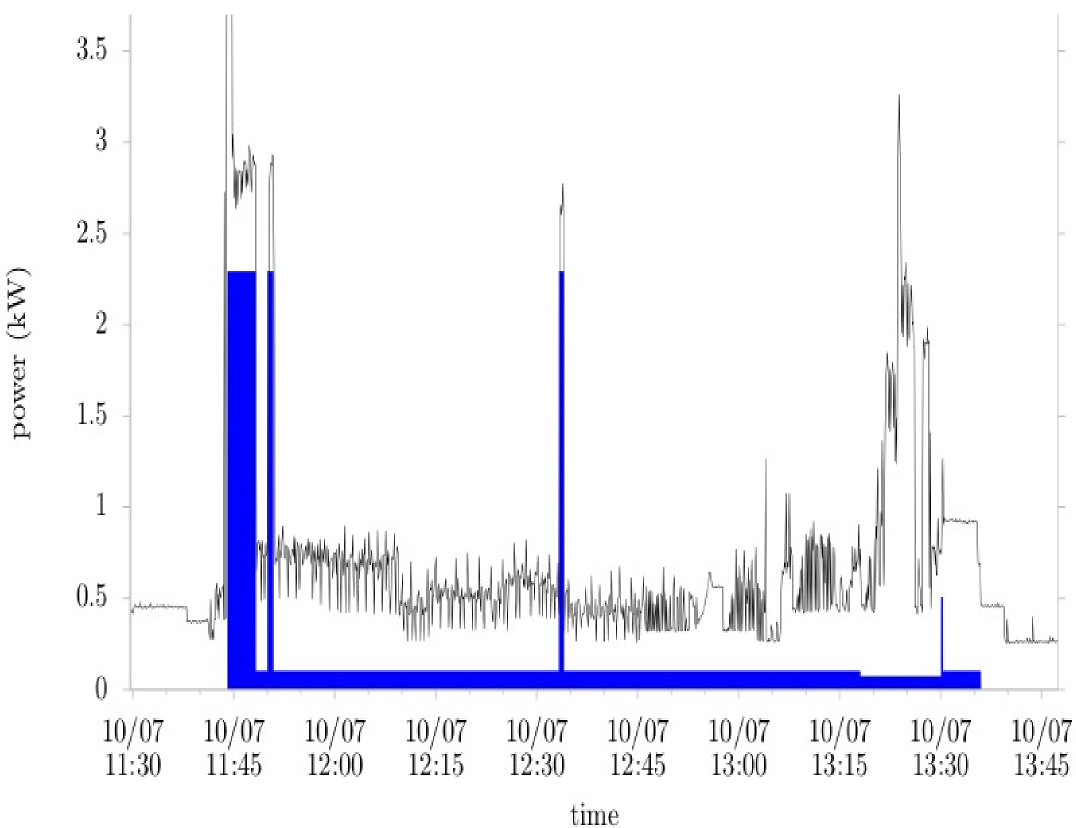


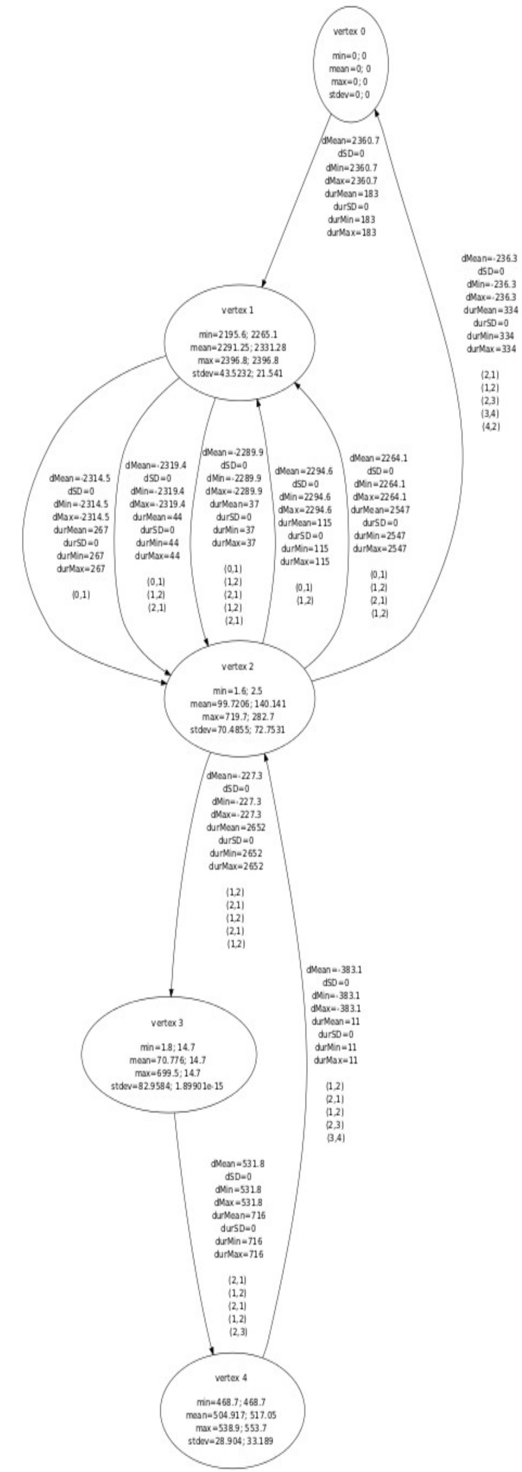
Time	Av likelihood	Correct?
08:15:08	0.89	Y
08:42:23	0.64	Y
08:55:38	0.50	Y
09:10:12	0.87	Y
09:27:48	0.90	Y
09:58:04	0.55	Y
10:30:32	0.75	Y
20:43:35	0.79	Y
22:08:21	0.83	Y

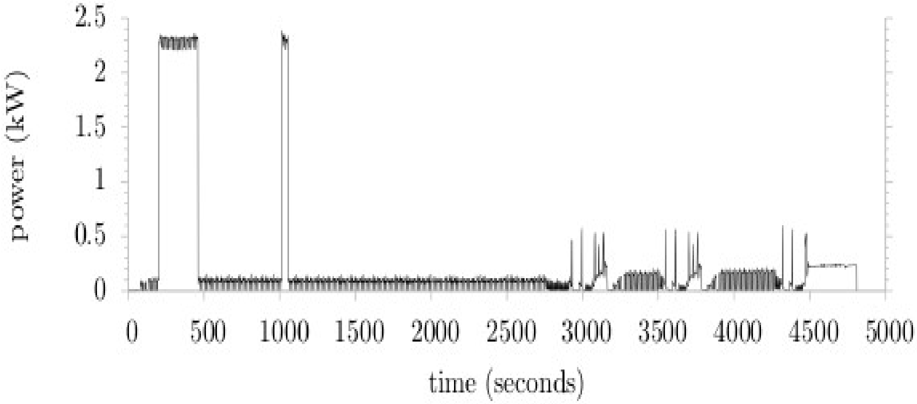




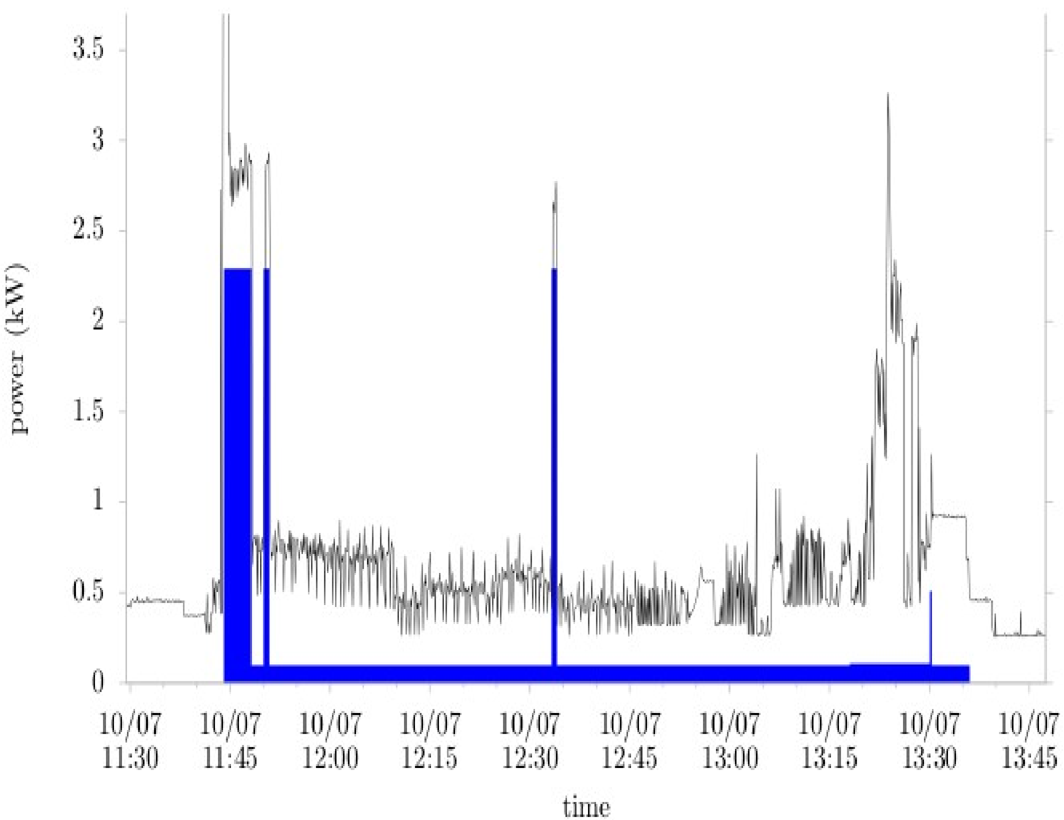
washer2.csv signature

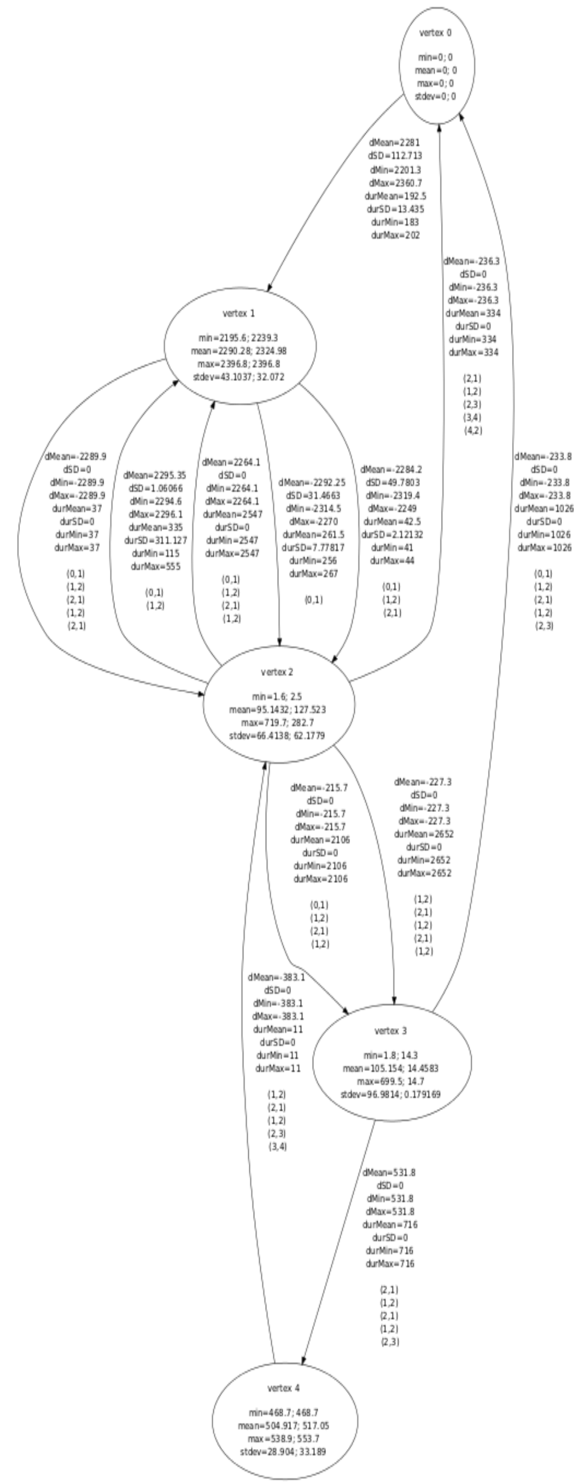




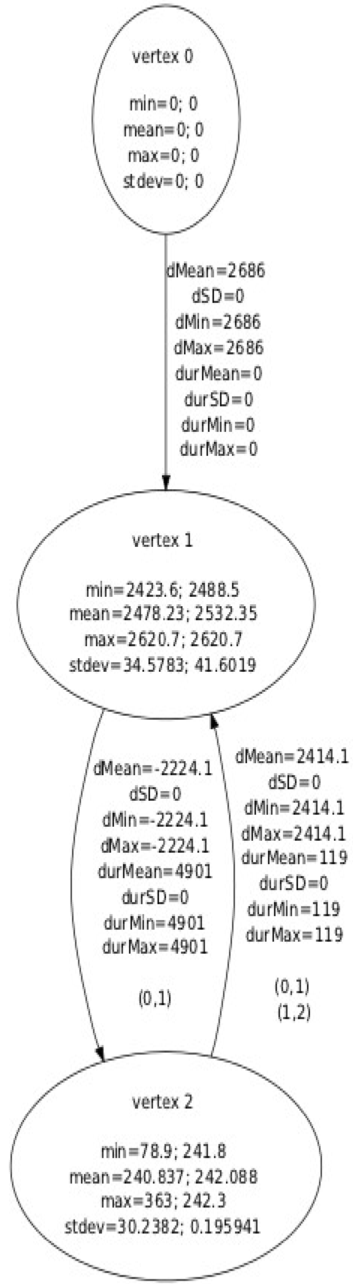


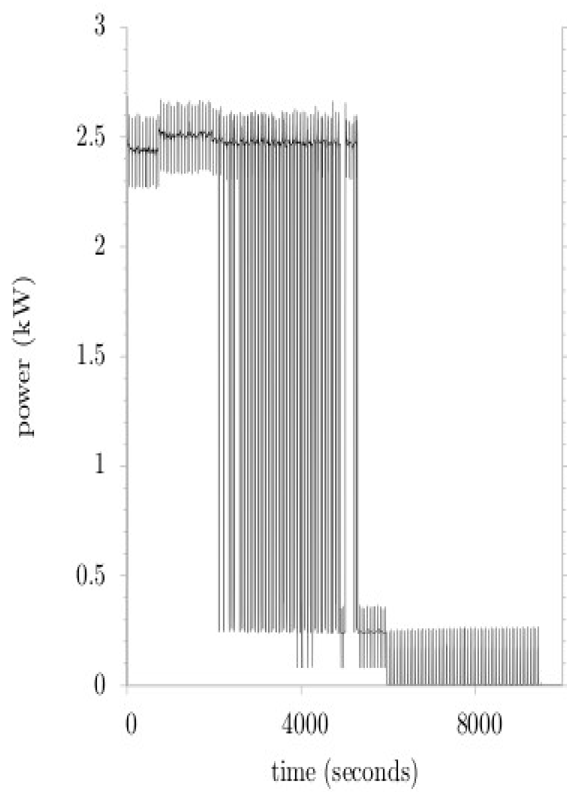
`washer.csv` signature.





Time	Av likelihood	Correct?
14:10:00	—	False neg





3 days of aggregate data (`earlyJuly.csv`)

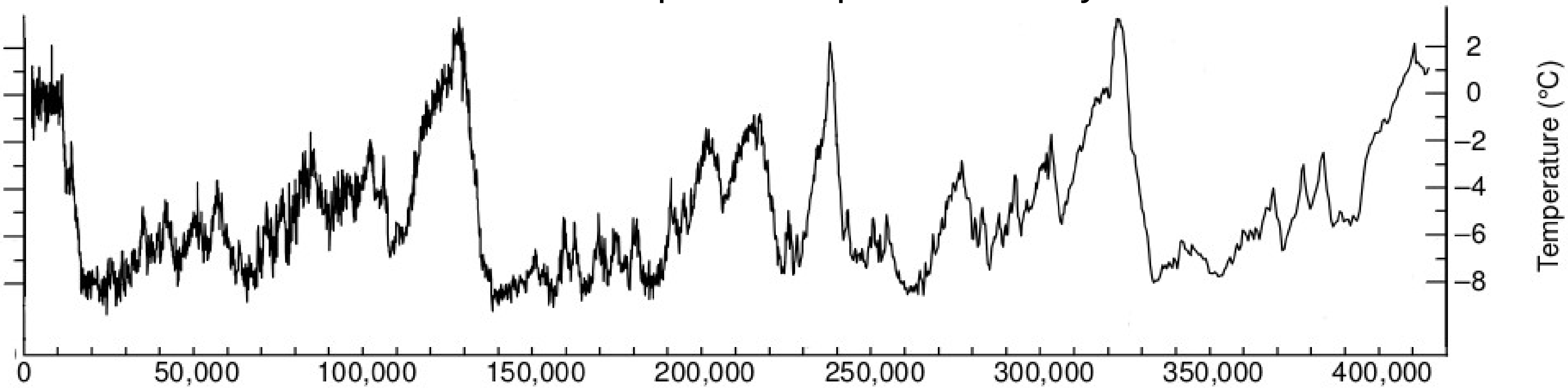
	% hits	failed to detect	false positives
Toaster	100 % (6 out of 6)		
Kettle	100 % (28 out of 28)		
Washer	100 % (4 out of 4)		1
Tumble	0 % (0 out of 2)	2	

10 days of aggregate data (`earlyAugust.csv`)

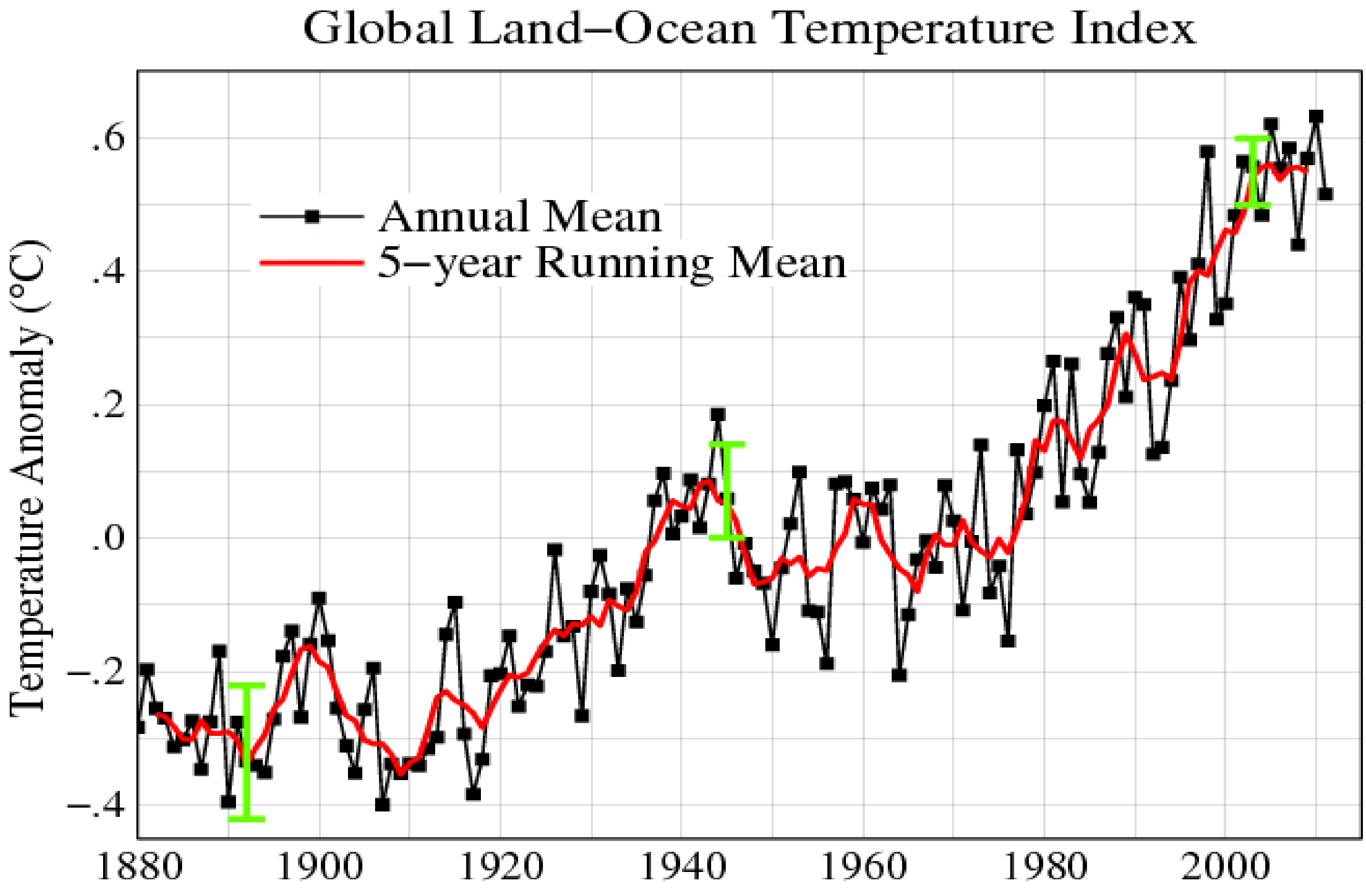
	% hits	failed to detect	false positives
Toaster	100 % (5 out of 5)		
Kettle	100 % (25 out of 25)		6
Washer	100 % (2 out of 2)		6
Tumble	0 % (0 out of 3)	3	

Limit warming to 2°C by 2100

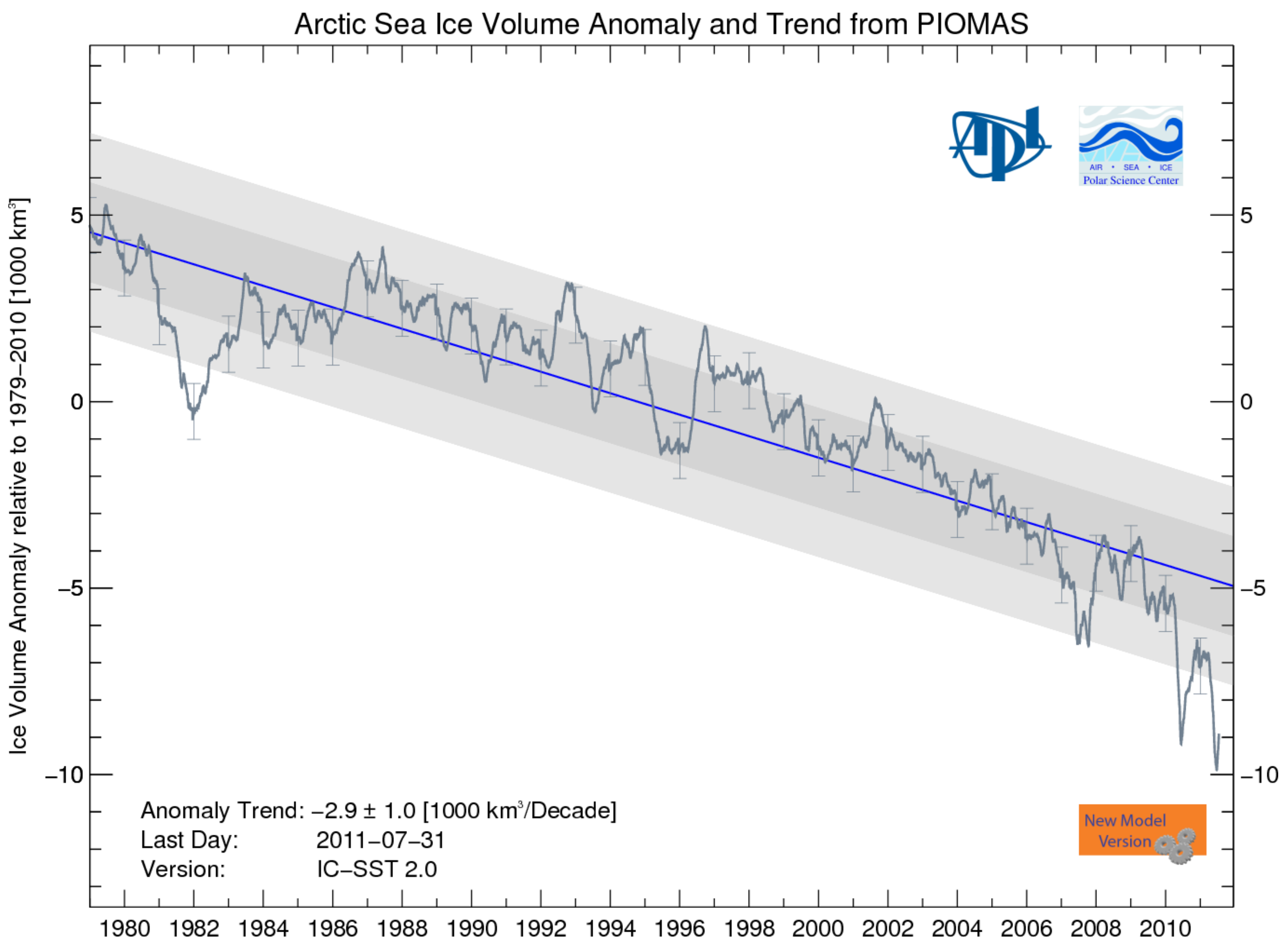
Surface temps for the past 420,000 years



Petit, J. R. and Jouzel, J. and Raynaud, D. and Barkov, N. I. and Barnola, J.-M. and Basile, I. and Bender, M. and Chappellaz, J. and Davis, M. and Delaygue, G. and Delmotte, M. and Kotlyakov, V. M. and Legrand, M. and Lipenkov, V. Y. and Lorius, C. and PEpin, L. and Ritz, C. and Saltzman, E. and Stievenard, M., "Climate and atmospheric history of the past 420,000 years from the Vostok ice core, Antarctica", Nature (1999), 429--436.

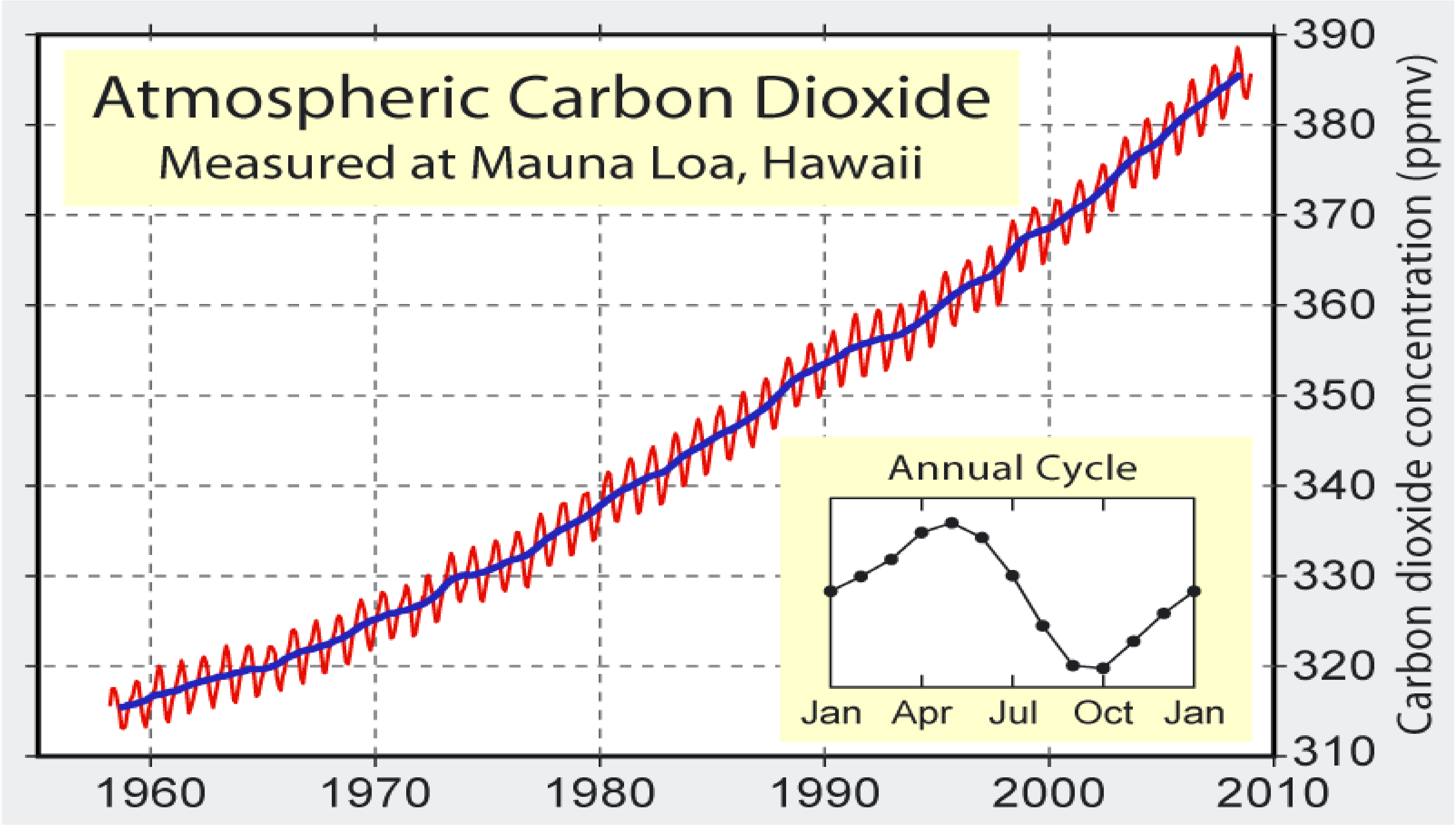


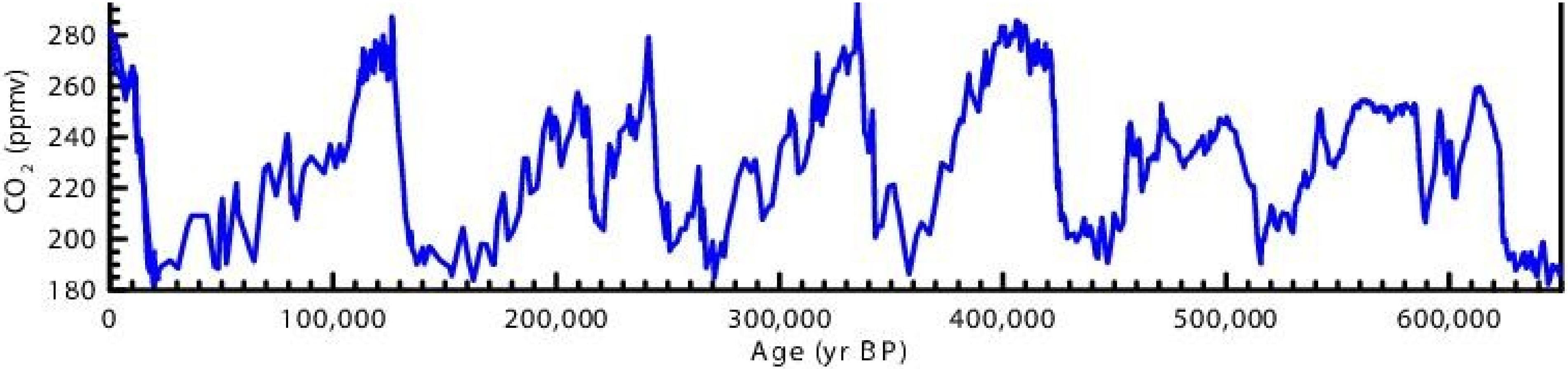
http://data.giss.nasa.gov/gistemp/graphs_v3/



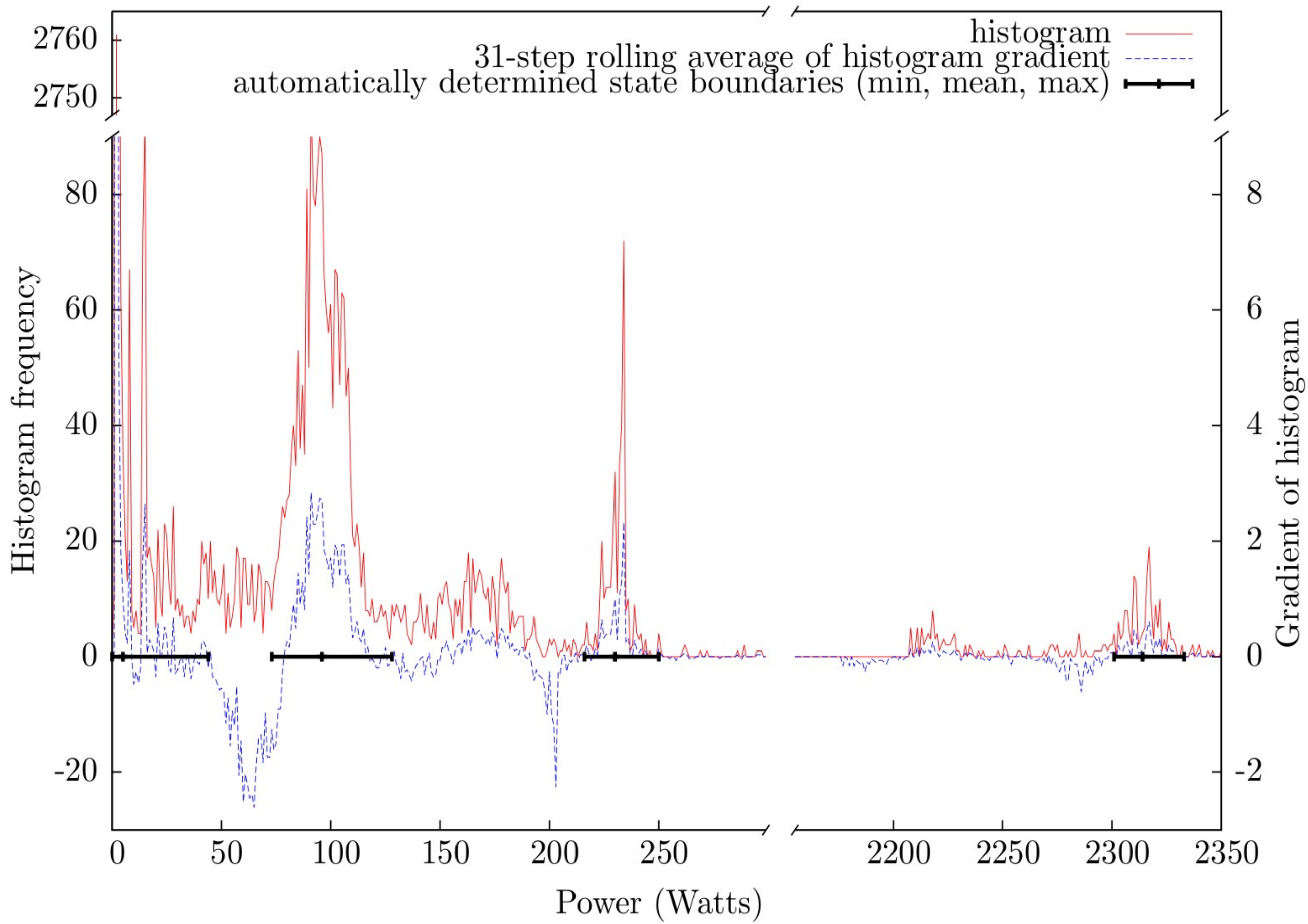
A y-axis value of about "-15" on the graph above corresponds to zero ice volume.
(PIOMAS = Pan-Arctic Ice-Ocean Modelling and Assimilation System)

Schweiger, Axel J and Lindsay, Ron and Zhang, Jinlun and Steele, Michael and Stern, Harry L. and Kwok, Ron,
"Uncertainty in Modeled Arctic Sea Ice Volume", Journal of Geophysical Research (2011).





Siegenthaler, U. et al. "Stable Carbon Cycle-Climate Relationship During the Late Pleistocene". Science 310, 1313 -1317 (2005).


histogram
31-step rolling average of histogram gradient
automatically determined state boundaries (min, mean, max)
Histogram frequency
Gradient of histogram
Power (Watts)
2760
2750
80
60
40
20
0
-20
8
6
4
2
0
-2
0
50
100
150
200
250
2200
2250
2300
2350