Fraunhofer Center for Sustainable Energy Systems

Disaggregation of Home Energy Display Data Using Probabilistic Approach

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International Conference on Consumer Electronics

Las Vegas

15 January 2012

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What Is Home Energy Display (HED)?

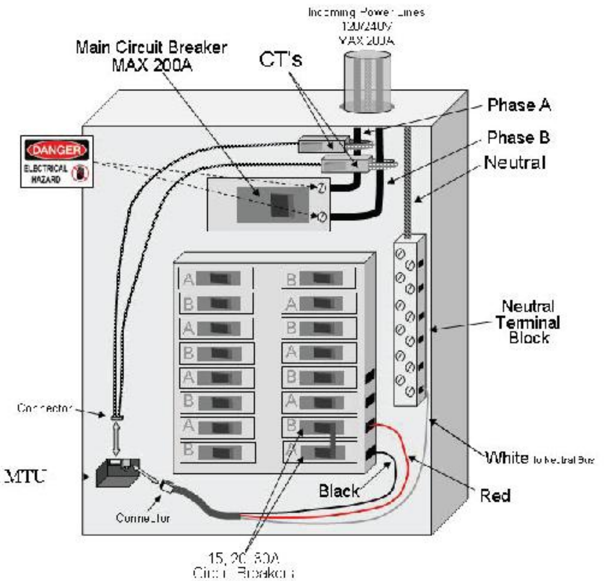
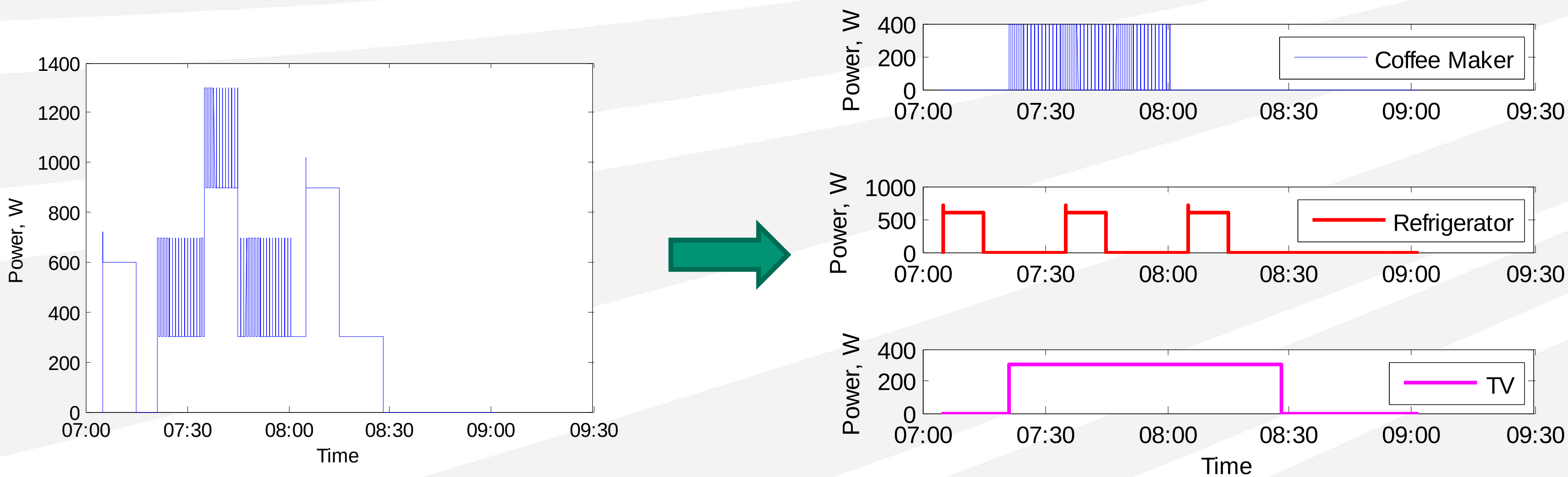


Fig. 3
Installing MTU Inside Panel
Typical Combination Circuit Breaker Panel

- Intended for home energy saving
- Information not actionable

What Is NIALM?

- Non-Intrusive Appliance Load Monitoring
  - A.k.a. Non-Intrusive Load Monitoring



- Main breaker/circuit level
- Data acquisition (hardware) and disaggregation algorithms (software)

NIALM: HED User Requirements

- Features: compatible with 1 Hz, real power only
- Accuracy: 80-90%
- No training
- Real-time capabilities
- Scalability (up to 20-30 appliances)
- Various appliance types

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NIALM: Types of Appliances

- ❑ Permanent

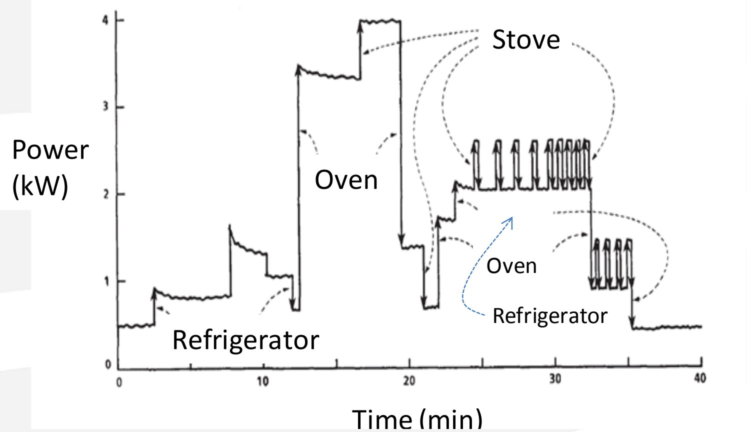
- ❑ On/off

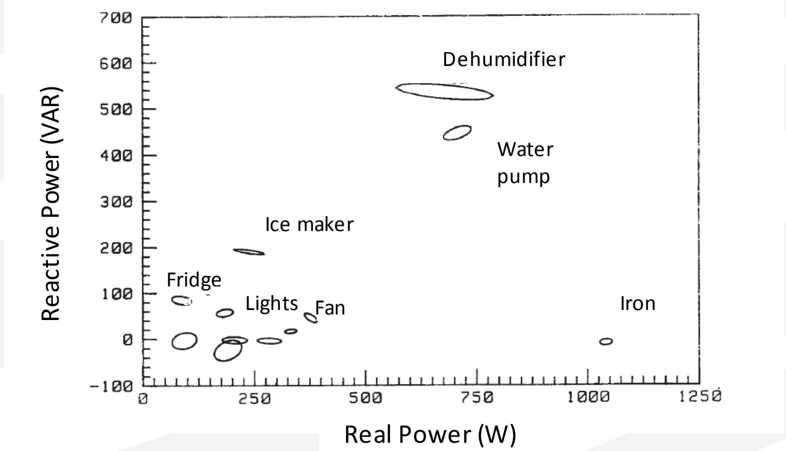
- ❑ Multi State

- ❑ Variable

Known NIALM Methods for HEDs: Basic Method

Hart, 1992 (MIT method)



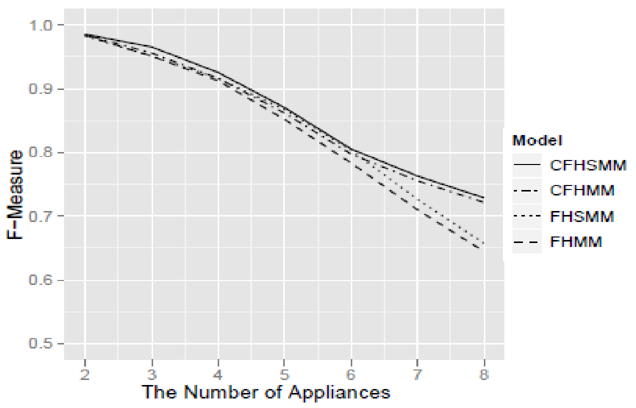


- Features: steady-state change of power (real and reactive)
- Changes of power identified and tracked
- Training
- Modifications to account for multi-state appliances
- Accuracy: ~70-80%
- Major problem: overlap in power draw

Known NIALM Methods for HEDs: Advanced Method

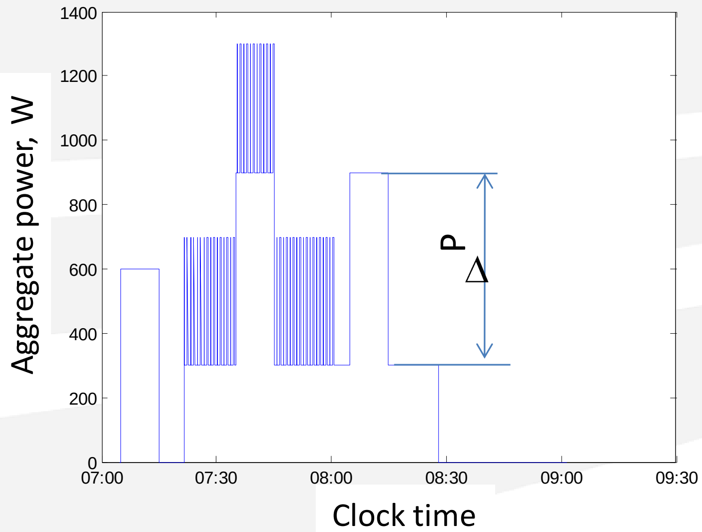
Kim, et al., 2011

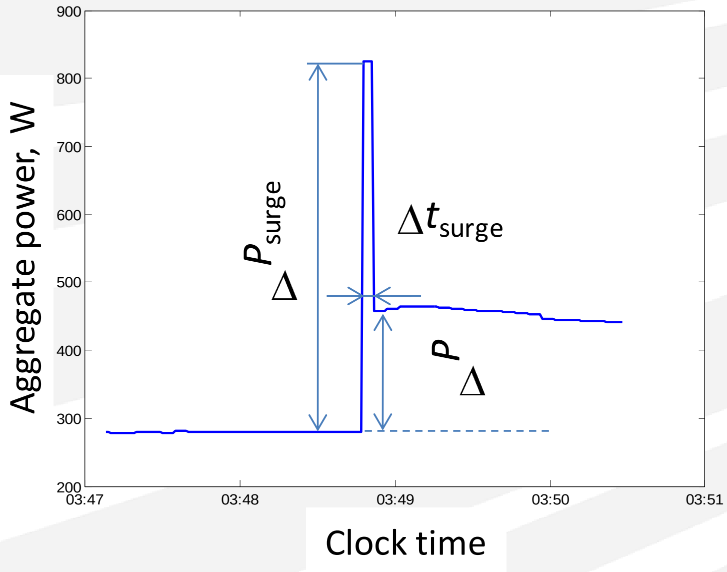
- Features: steady-state change of power and time-on statistics
- Factorial hidden Markov model (FHMM) – mixture of independent 2-state chains coupled through observations
- No training but number of appliances must be known
- Need to process all the data (every second) for all appliances
- Exponential computational complexity, cannot work with > 10 appliances
- Overlap - alleviated
- Accuracy: ~70-80%



Proposed Method: Features

- ❑ Power-related

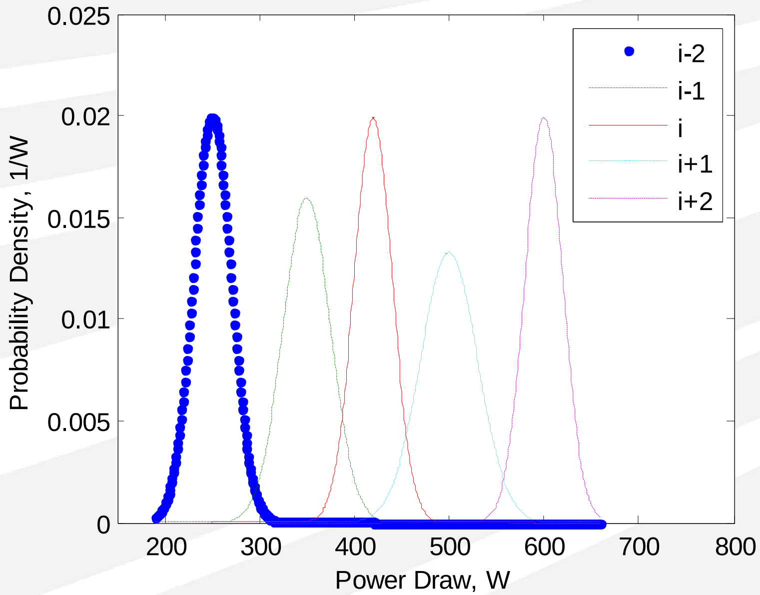




- ❑ Time-related
  - ➢ Time-on, time-off statistics
  - ➢ Can be conditional on time of day

Proposed Method: Key Idea

- ❑ Order appliances by power draw
- ❑ Consider appliance tuplets, e.g., i ±1
- ❑ Track tuplets separately in time
- ❑ Tuplet size – 3, or even 2 (triplet split in two)
- ❑ Foreign and missing data



Transitions within a Tuplet

Tuplet size: 2

System states

State	Appliance i	Appliance $(i+1)$
1	Off	Off
2	On	Off
3	Off	On
4	On	On

Negative power change, system transitions

Transition between states	Underlying event(s)
1,1	Is foreign datum
1,2	Was missing datum from state 2 and is foreign datum
1,3	Was missing datum from state 3 and is foreign datum
1,4	Were missing data from states 2 and 3 and is foreign datum
2,1	Appliance i is turning off but appliance $(i+1)$ has not turned on
2,2	Is foreign datum
2,3	Was missing datum from state 4 and is 4,3 transition
2,4	Was missing datum from state 4 and is external datum
3,1	Appliance $(i+1)$ is turning off but appliance i has not turned on
3,2	Was missing datum from state 4 and is 4,2 transition
3,3	Is foreign datum
3,4	Was missing datum from state 4 and is foreign datum
4,1	Was missing datum from either state 2 or 3 and is 2,1 or 3,1 transition
4,2	Appliance $(i+1)$ is turning off but appliance i has not turned off
4,3	Appliance i is turning off but appliance $(i+1)$ has not turned off
4,4	Is foreign datum

- Example of transition probability:

$$P_{4,2} \propto p_{i+1}(\Delta P)\, f_{i+1}(\tau_{i+1,on})[1-F_i(\tau_{i,on})]$$

Modified Viterbi Algorithm

$$\{\hat{s}_t\} = \underset{\{s(t)\}}{\arg\max}[\{s_t\} \mid \{\omega_t)\}]$$

$\{\hat{s}_t\}$ - maximum likelihood estimation of state sequence

$\{s_t\}$ - state sequence

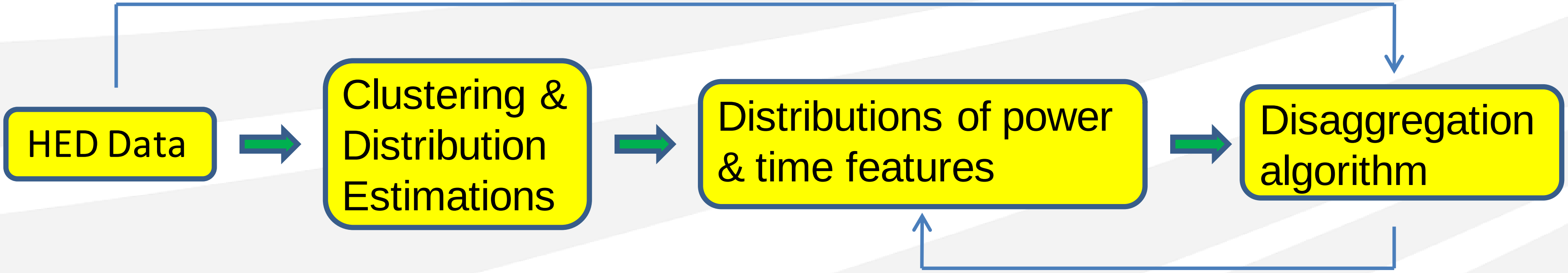
$\{w_t)\}$ - transition observations' sequence

- Developed for 1-st order Hidden Markov models
- Our model can be of higher order
- Keep in memory previous state for each appliance in tuplet

Estimation of Power and Time Distributions

- ❑ Historical data (~ two weeks)
- ❑ Clustering negative power changes (ISODATA)
- ❑ Matching negative and positive changes, power surges
- ❑ Estimation of time-on and time-off durations
- ❑ Statistical modeling of all distributions

High-Level Block Scheme



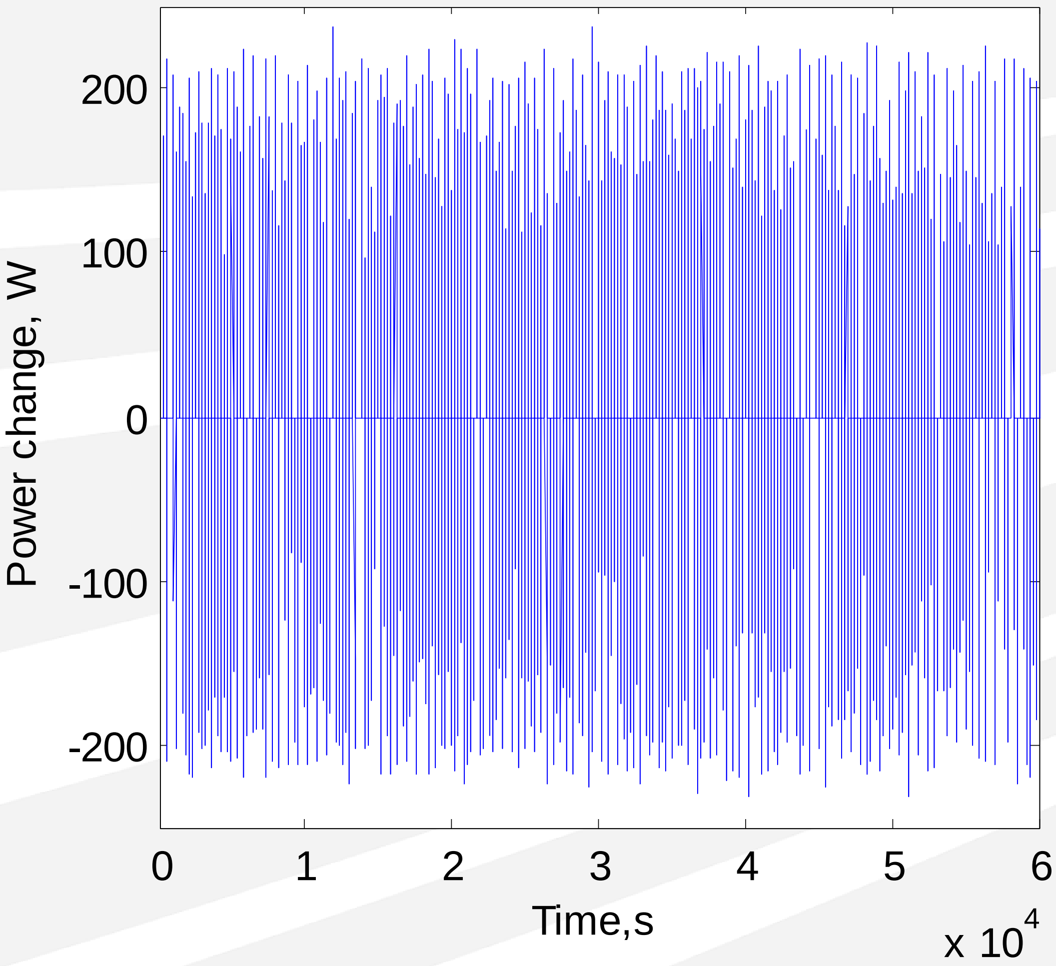
Simulation Example

- 5 on-off overlapping appliances
- Normal (Gaussian) distributions of power changes
- Uniform distributions of time-on and time-off

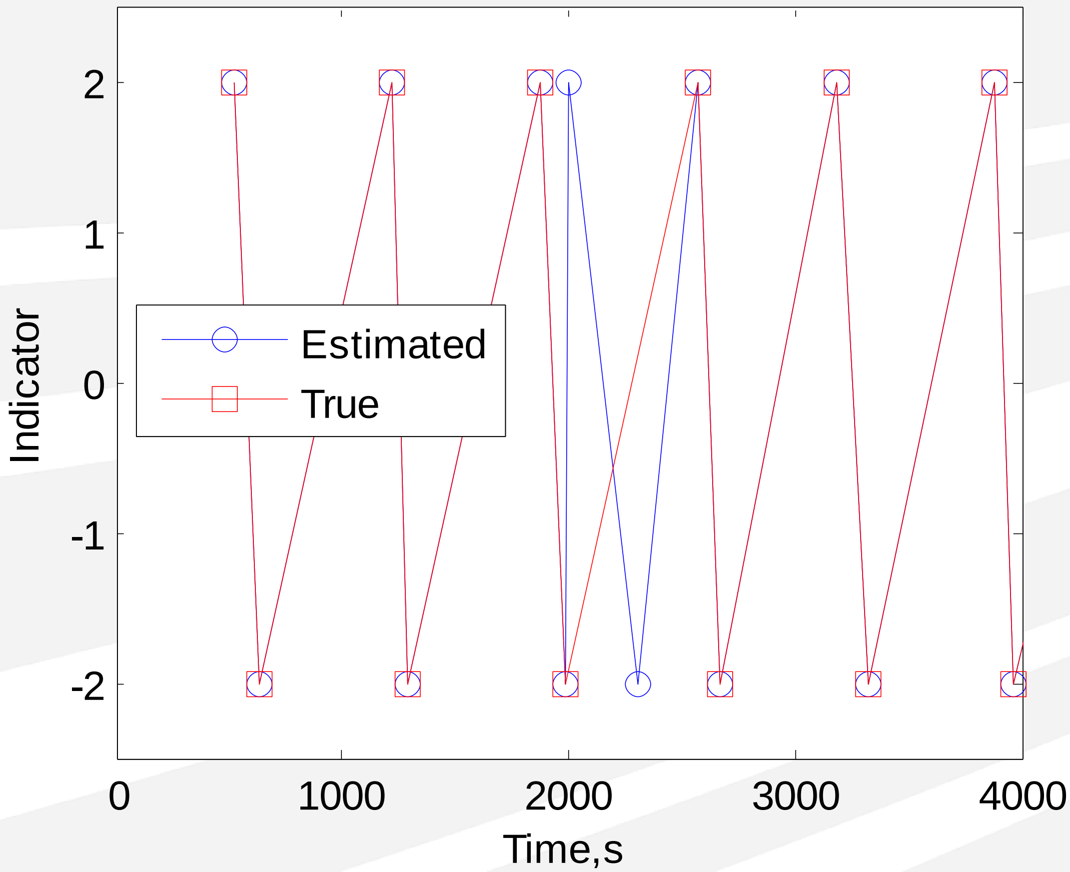
Simulated appliance	Mean M, positive change, W	Mean M, negative change (absolute value), W	Standard deviation Σ, W
1	110	105	10
2	130	135	13.5
3	150	160	10
4	180	190	13.5
5	210	210	10

Simulated appliance	Time-on, minimum, s	Time-on, maximum, s	Time-off, minimum, s	Time-off, maximum, s
1	30	100	400	600
2	70	150	500	600
3	100	180	350	500
4	150	270	200	400
5	40	140	300	700

Simulated Time Series



Simulated Time Series: Disaggregation Results



Indicator = ±2 → Appliance 2 is on(off)

Simulated Time Series

- Accuracy metric: F-measure

$$F = 2\frac{\frac{TP}{TP+FP}\cdot\frac{TP}{TP+FN}}{\frac{TP}{TP+FP}+\frac{TP}{TP+FN}}$$

Simulated Appliance	Bayesian Classifier	Our Algorithm, no time-off statistics used	Our Algorithm
1	0.859	0.910	0.985
2	0.666	0.835	0.865
3	0.749	0.850	0.925
4	0.743	0.865	0.970
5	0.859	0.950	0.965

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Real Household Data by HED

- Kolter and Johnson (2011) collected data in six households in Massachusetts
- Submetered on individual circuit level
- Selected 1 household with 9 "good" circuits recorded over 26 days

Circuit (appliance)	Positive, mean, W	Positive, standard deviation, W	Negative, mean, W	Negative, standard deviation,W
1 Refrigerator	204.3	3.9	179.5	2.4
2 Dishwasher	217.3	20.6	212.1	19.7
3 Kitchen outlet 1	1084.8	14.5	1074.6	15.1
4 Microwave	1548.5	52.4	1504.9	43.9
5 Kitchen outlet 2	1543.5	21.1	1533.5	14.5
6 Bathroom GFI	1613.2	18.6	1607.3	18.4
7 Oven 1	1651.4	22.4	1640.7	21.1
8 Oven 2	2474.9	29.5	2448.4	24.2
9 Kitchen outlet 3	2767.9	51.3	2706.3	33.1

Real Household Data: Appliance Characteristics

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Real Household Data: Disaggregation Results

Appliance from Table VI	Bayesian classifier	Our algorithm
1 Refrigerator	0.859	0.831
2 Dishwasher	0.881	0.846
3 Kitchen outlet 1	0.989	0.936
4 Microwave	0.775	0.899
5 Kitchen outlet 2	0.409	0.840
6 Bathroom GFI	0.753	0.927
7 Oven 1	0.800	0.908
8 Oven 2	1.0	0.962
9 Kitchen outlet 3	1.0	0.971

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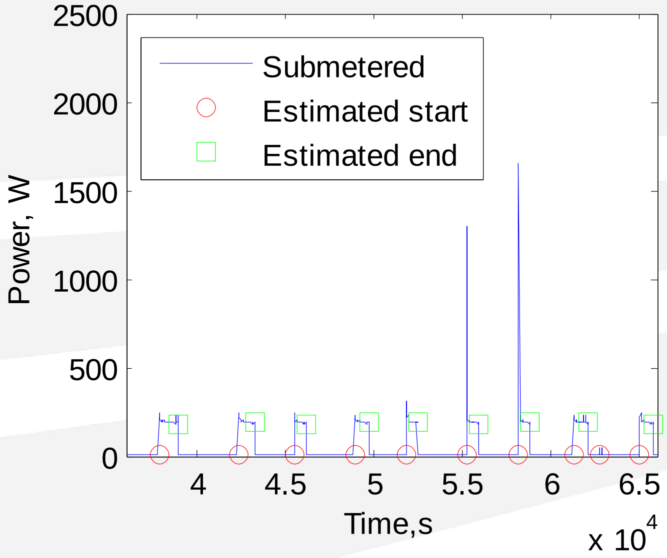
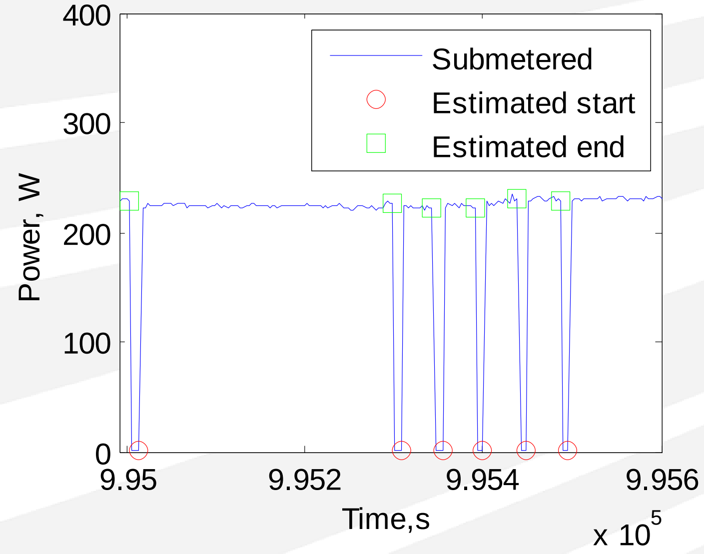
Real Household Data: Disaggregation Results

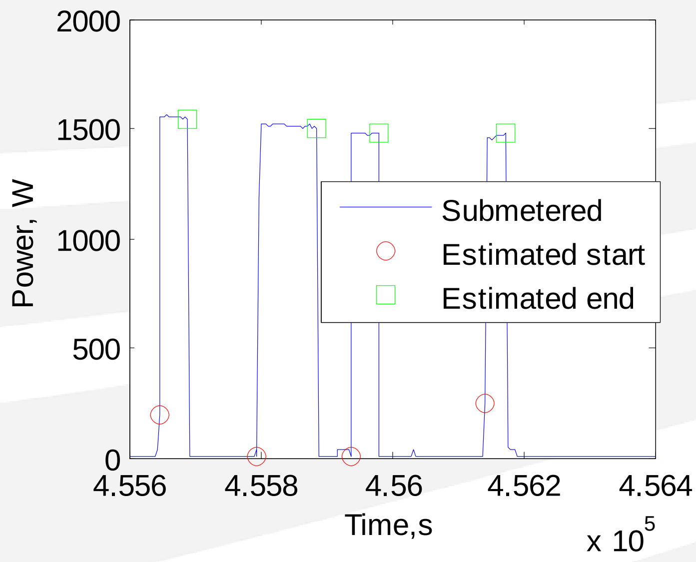


1. Refrigerator

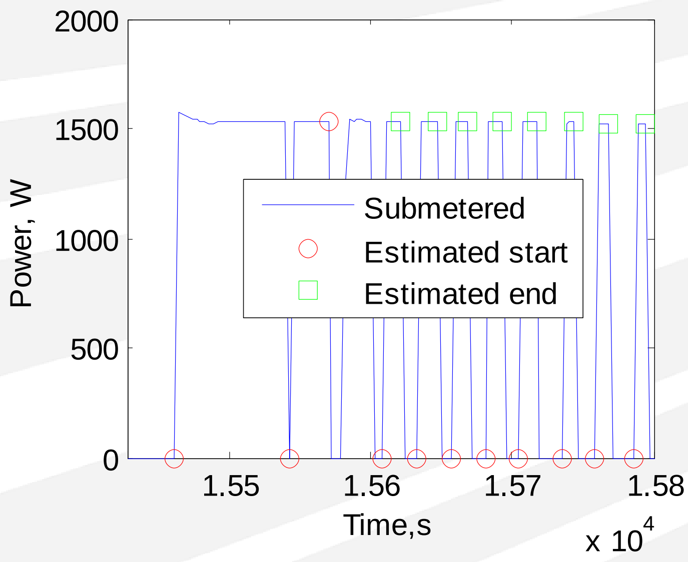


2. Dishwasher

Real Household Data: Disaggregation Results



4. Microwave



5. Kitchen outlet 2

Needs Improvement

- ❑ Fully develop triplet
- ❑ Better pre-processing (filtering, incremental power changes)
- ❑ Better change detection (change-point problem)
- ❑ More advanced clustering procedure
- ❑ Matching between found clusters and real appliances (use of estimated time-on and time-off features)

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Conclusions

Use Requirements	Our Method
❑ Features: compatible with 1 Hz, real power only	❑ Yes
❑ Accuracy: 80-90%	❑ Accuracy: 80-90%
❑ No training	❑ Learning from historical data. Matching with real appliances forthcoming
❑ Real-time capabilities	❑ Yes
❑ Scalability (up to 20-30 appliances)	❑ Yes. Complexity linear with number of appliances
❑ Various appliance types	❑ Not yet, but in the process