

Non-Intrusive Load Monitoring: A Power Consumption Based Relaxation

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Introduction

■ NILM challenges

- Training
- Modeling large number of devices

■ Power Consumption Clustered NILM (PCC-NILM)

- Group devices by power consumption
- Report on energy consumed by each class of devices
 - Instead of full disaggregation problem



NILM Background

- George Hart, MIT
 - First posed NILM problem in early-mid 1980's
 - PQ-plane for clustering devices
 - Complete system for tracking energy
 - Finite State Machines (FSM) for tracking device operation
 - Could only handle on/off devices
 - Proposed methods for learning multi-state FSMs
 - Event-based framework

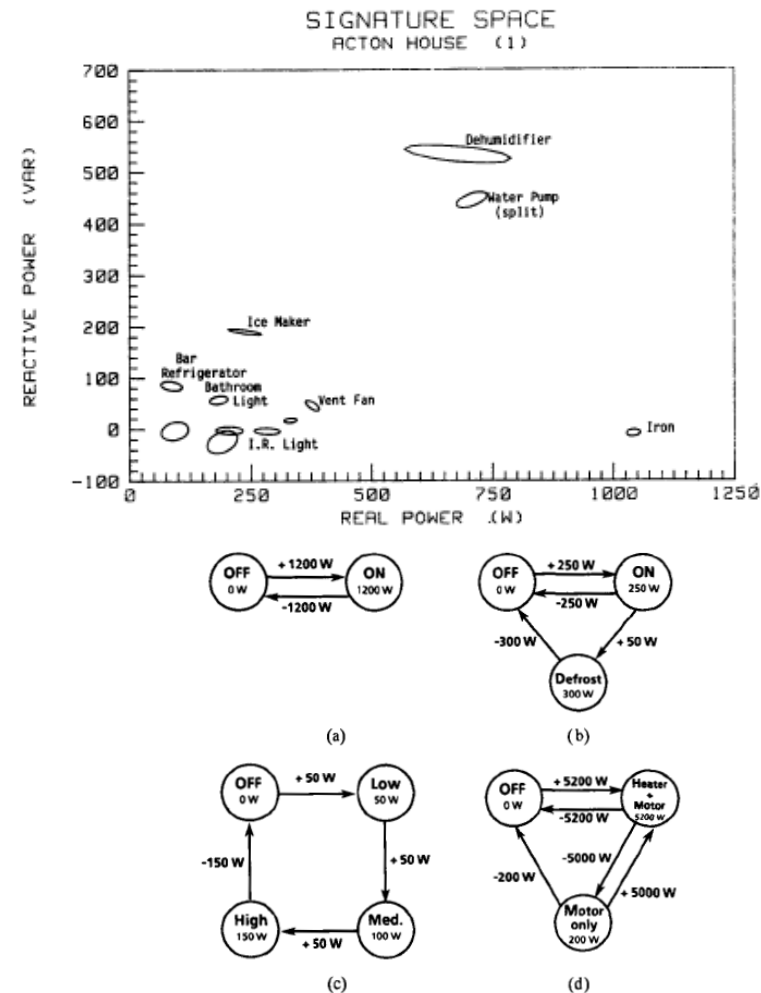
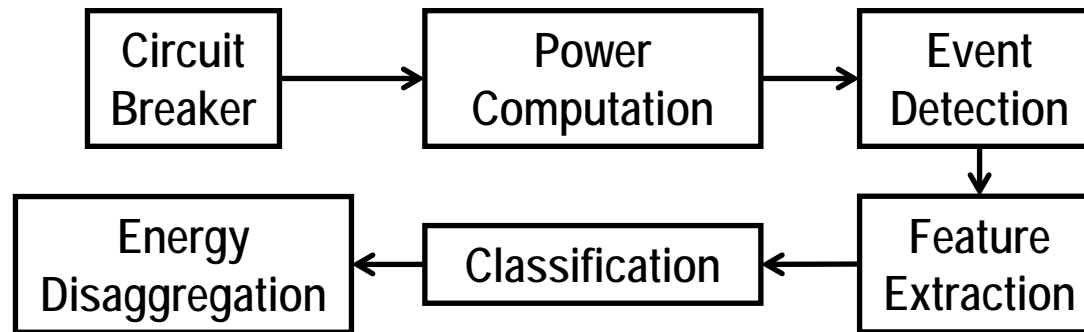


Fig. 4. Finite-state appliance models: (a) generic 1200 W two-state appliance, e.g., toaster; (b) refrigerator with defrost state; (c) "three-Way" lamp; (d) clothes dryer.

NILM Background

■ Traditional event-based NILM framework



■ Research after Hart, mid-1990's until 2011

- Focus on event detection, feature extraction, and classification
- Almost no work on **energy** disaggregation
 - Zeifman NILM review paper in 2011^[1]
 - Apart from Hart, only one author mentioned energy metrics
 - Berges Ph.D. Thesis^[2] proposes Energy Identification Ratio (EIR) metric

[1] M. Zeifman and K. Roth, "Nonintrusive appliance load monitoring: Review and outlook," *IEEE Transactions on Consumer Electronics*, vol. 57, no. 1, pp. 76–84, Feb. 2011.

[2] M. Berges, "A framework for enabling energy-aware facilities through minimally-intrusive approaches," Ph.D. Thesis, Carnegie Mellon University, 2010.

Event Detection Parameter Sweep

■ Log-Likelihood Ratio Event Detector

- 3 degrees of freedom
- 1,456 parameter combinations
- Fast algorithm

■ BLUED Dataset

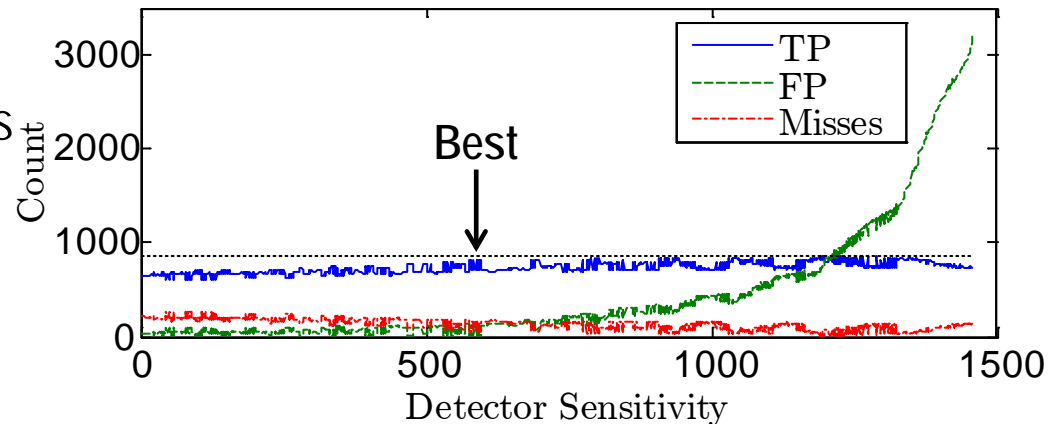
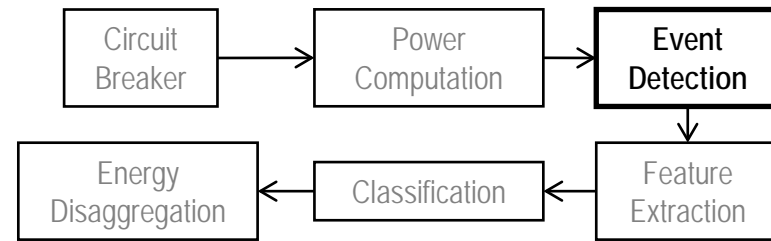
- Power sampled at 1 Hz
 - 867 phase A events
 - 1,588 phase B events

■ Detector Sensitivity

- Ordering based on total number of events detected

■ Best Detector

- Based on $\frac{TP}{E}$ vs. $\frac{FP}{E}$ [1]

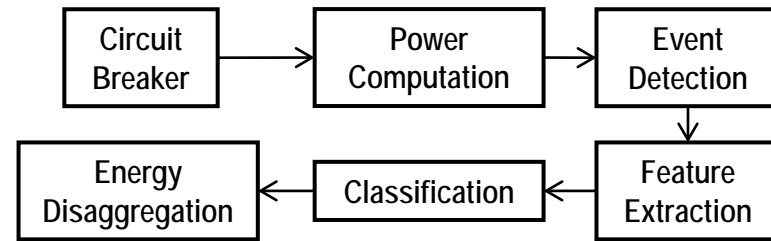


Sensitivity	Events	TP	FP	Misses
Least	681	646	35	221
Most	3972	736	3236	131
Most TP	1762	856	906	11
Least FP	750	743	7	124
Best	829	814	15	53

How to track energy with so many misses and false positives?

[1] K. Anderson et al., "Event detection for nonintrusive load monitoring," in Proceedings of the 38th Annual Conference on IEEE Industrial Electronics Society (IECON). Montreal, Canada: IEEE, Nov. 2012.

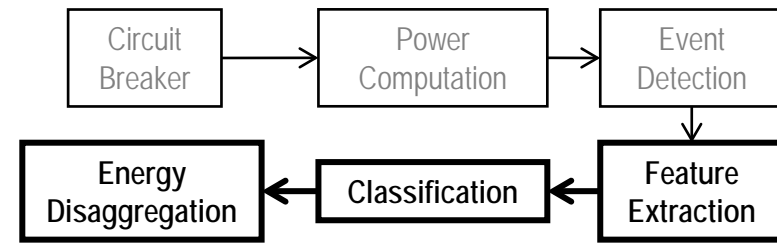
Event-Based NILM



- Difficulties with traditional event-based approach
 - Training
 - Lack of accepted performance metrics
 - Event detection, classification, energy consumption, etc.
 - Lack of energy disaggregation
 - Work on event detection and classification but little energy tracking
 - Cascading effect of errors from event detection and classification stages

Step back and reconsider the NILM problem...

Reconsidering the Disaggregation Problem



- Additive energy disaggregation model

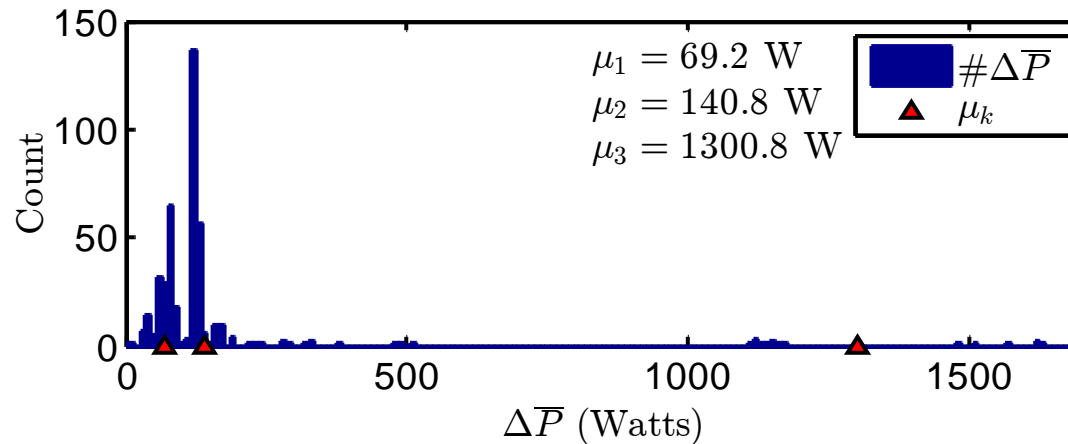
$$E = \sum_{k=1}^K E_k$$

- Total energy consumed is sum of energy consumed by K devices
- What if we allow K to represent something else?
 - Number of rooms
 - Activities
 - People

Need a data-driven solution...

Power Consumption Clustering

- Histogram of 'On' events from phase A of the BLUED dataset



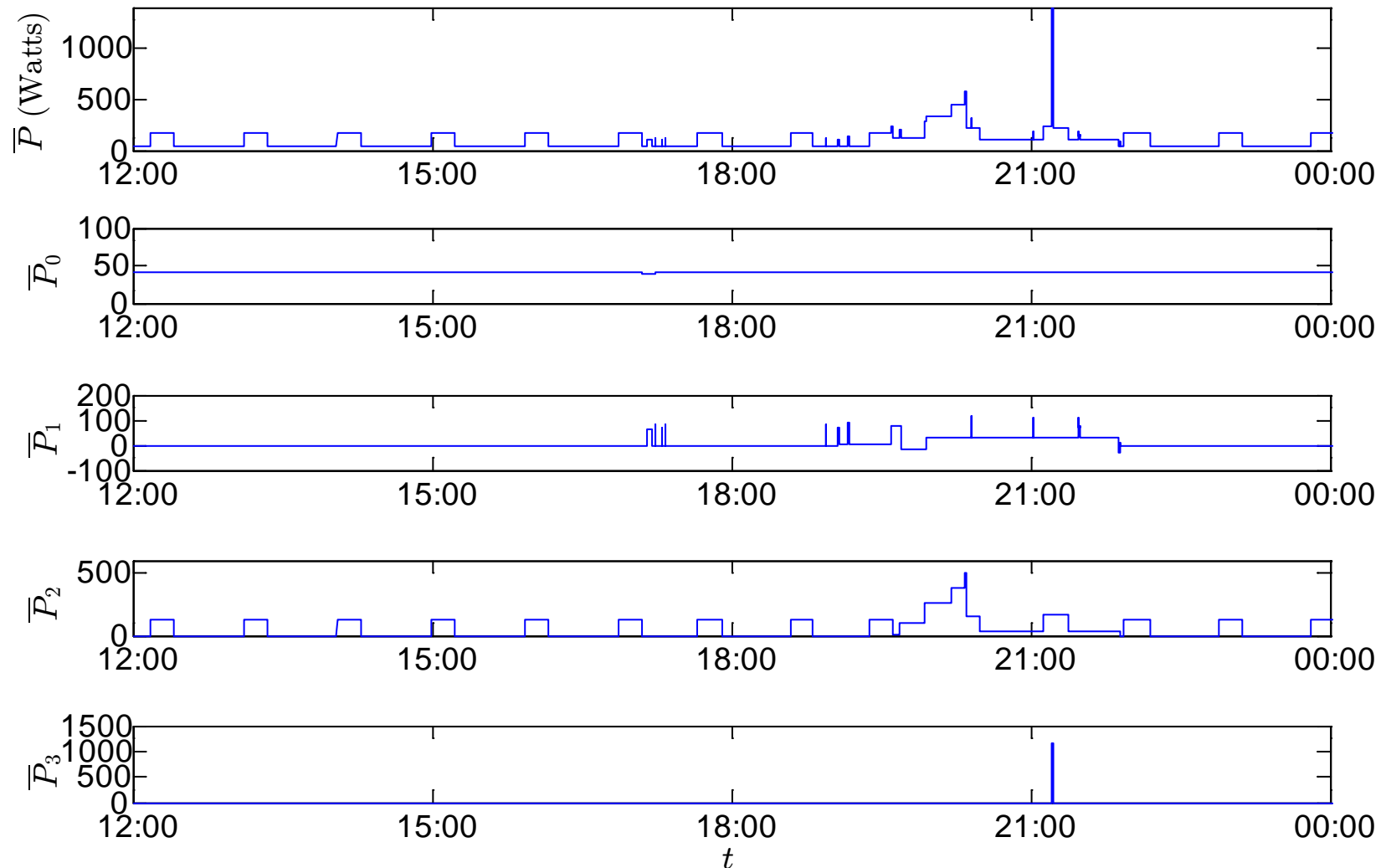
- Cluster centroids μ_k
- Track energy consumed by each class
 - Devices may be inferred from power ranges
 - Can track energy consumed by each class

$$E = E_0 + \sum_{k=1}^K E_k$$

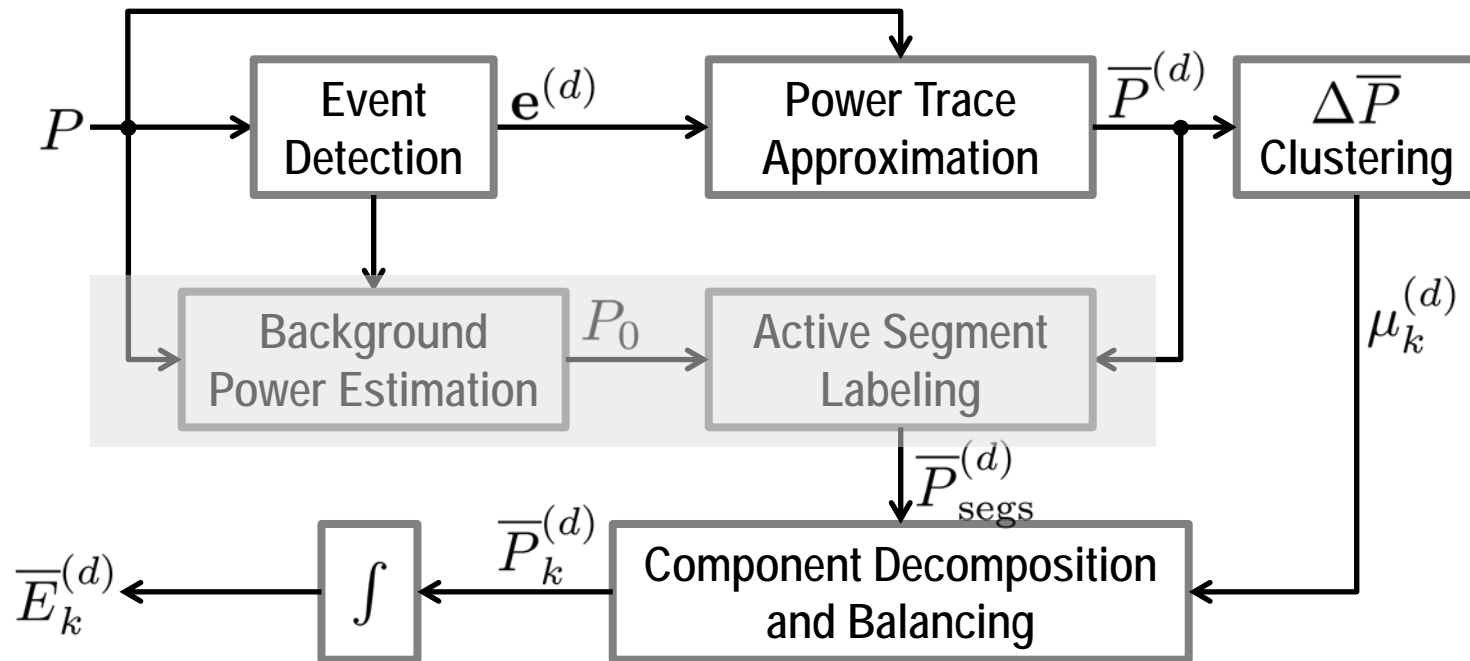
k	μ_k	Power Consumption Range
0	-	Background
1	69.2 W	0–105 W
2	140.8 W	105–720 W
3	1300.8 W	720+ W

PCC-NILM Solution Example

$$\bar{P} = \bar{P}_0 + \sum_{k=1}^K \bar{P}_k$$

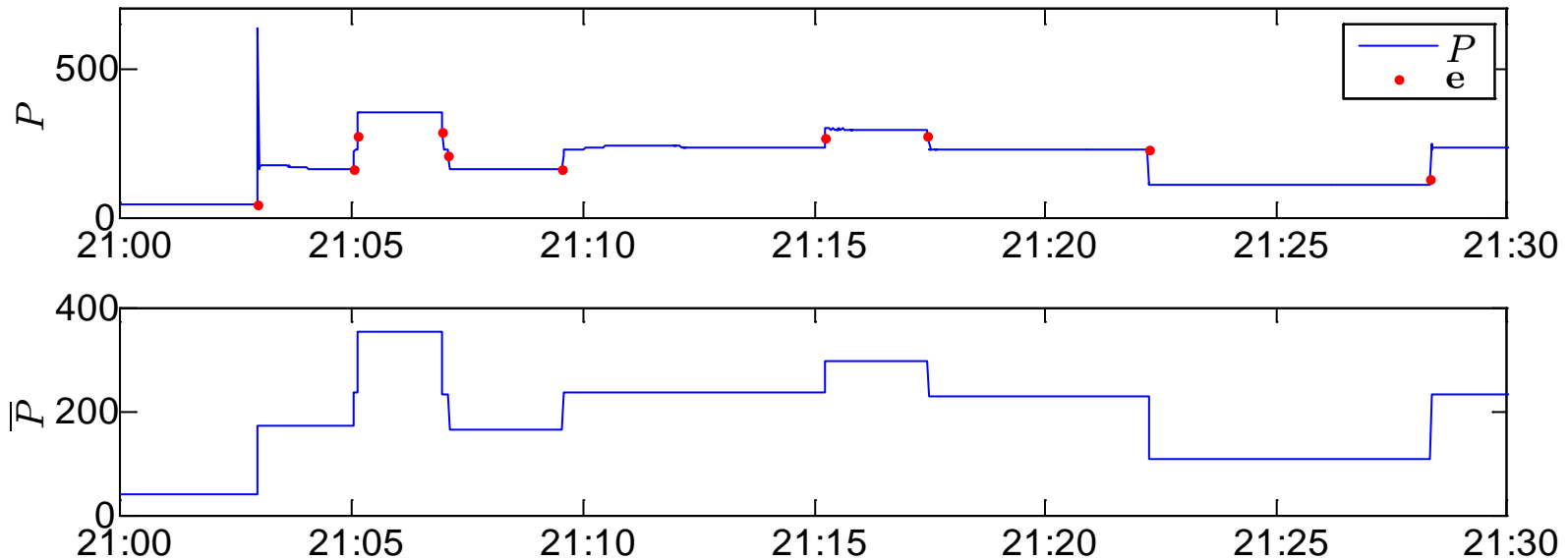


Approximate Power Trace Decomposition Algorithm (APTDA)



Power Trace Approximation

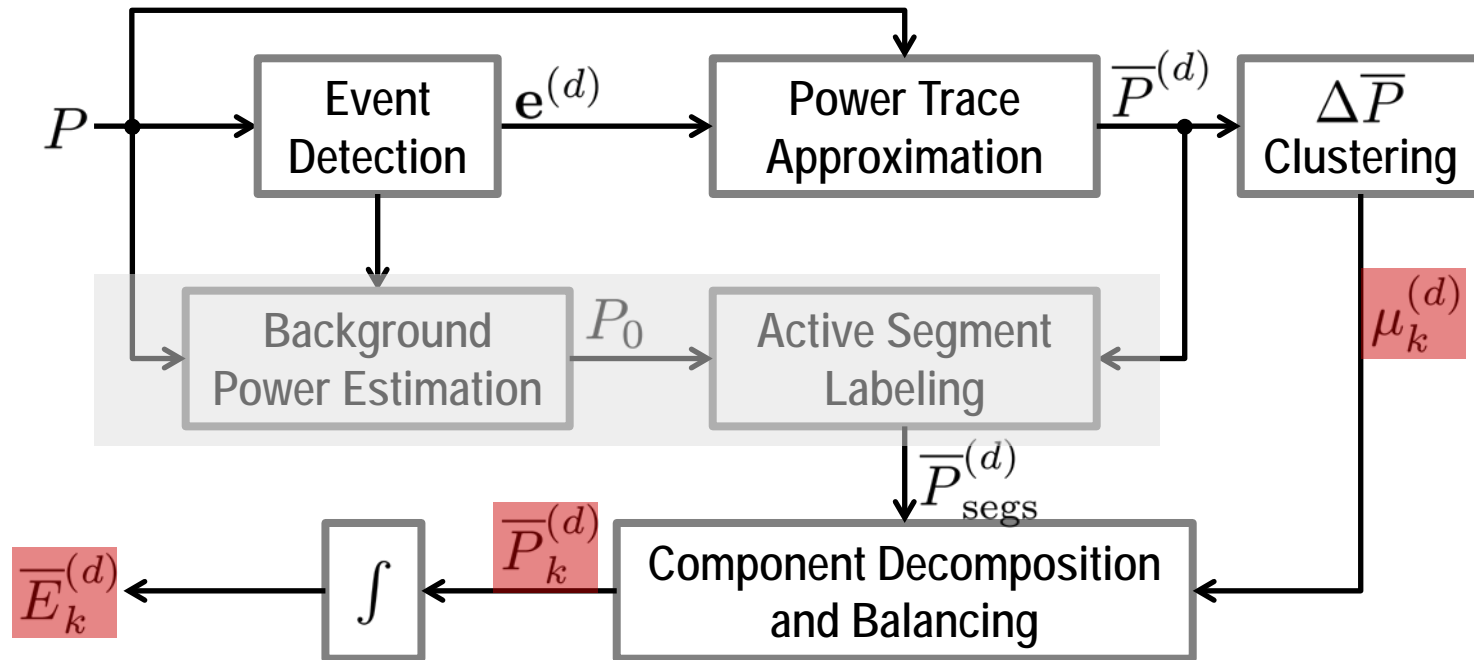
- Energy-preserving piecewise constant approximation, \bar{P}
 - Computed from original power trace, P , and set of edges, e



- \bar{P} is average of each segment of P^t
 - Segments are disjoint

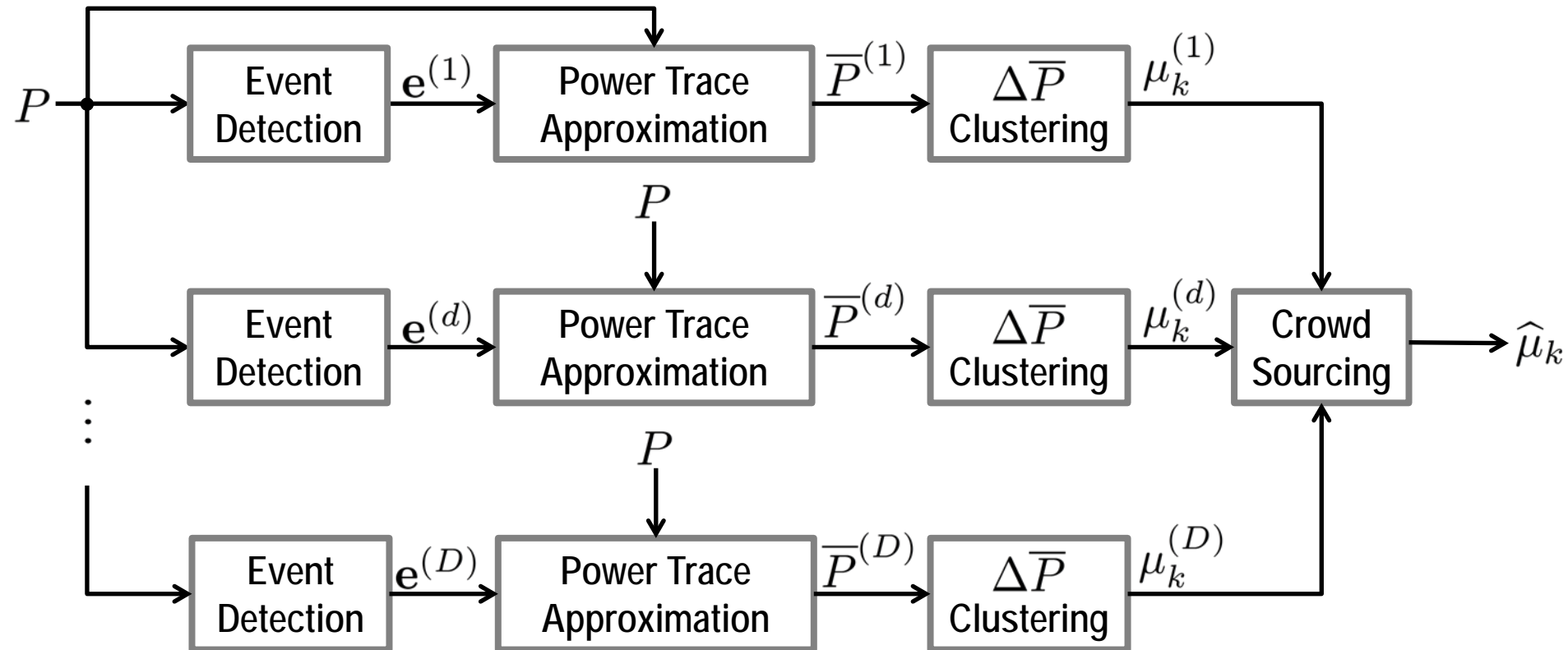
$$E_P = \int P dt = \int \bar{P} dt = E_{\bar{P}}$$

Approximate Power Trace Decomposition Algorithm (APTDA)

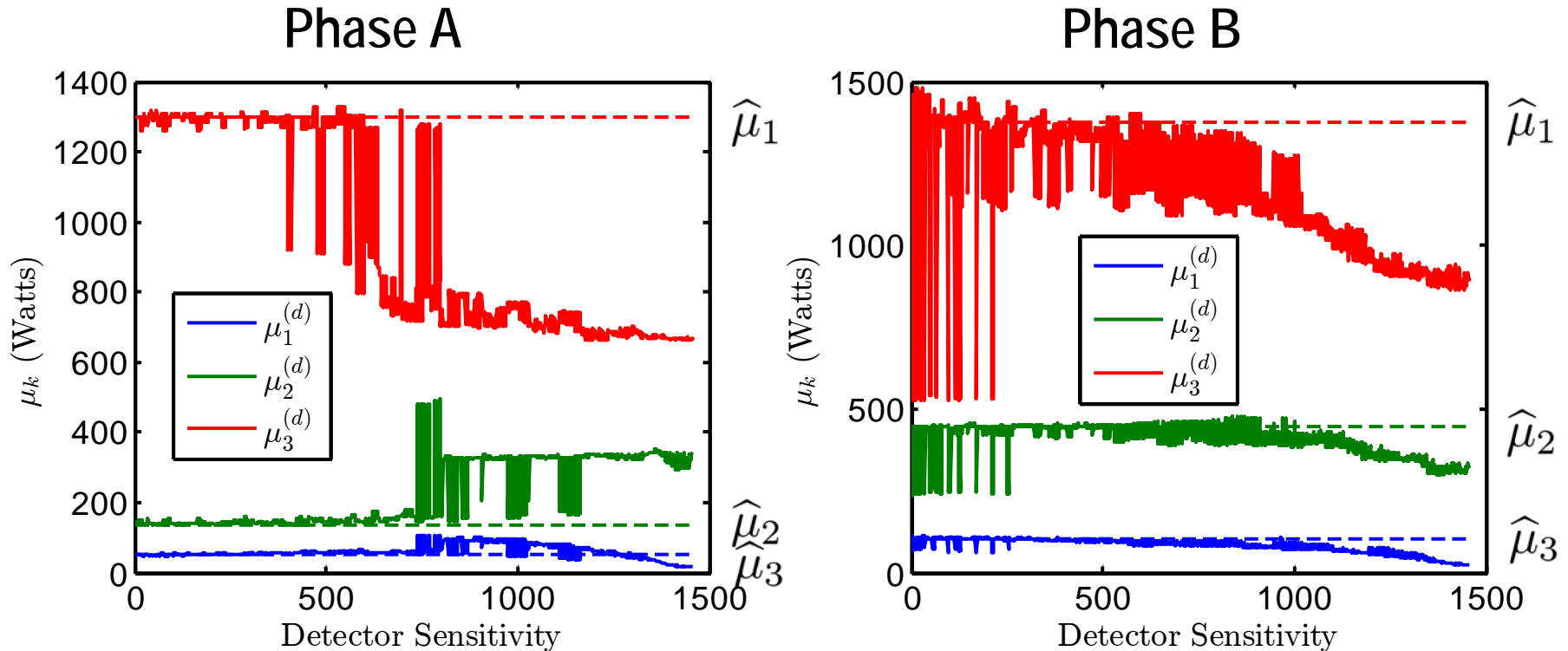


- Crowdsourcing event detectors
 - Compare results across wide range of detectors
 - Choose most stable output

Crowdsourcing Power Ranges

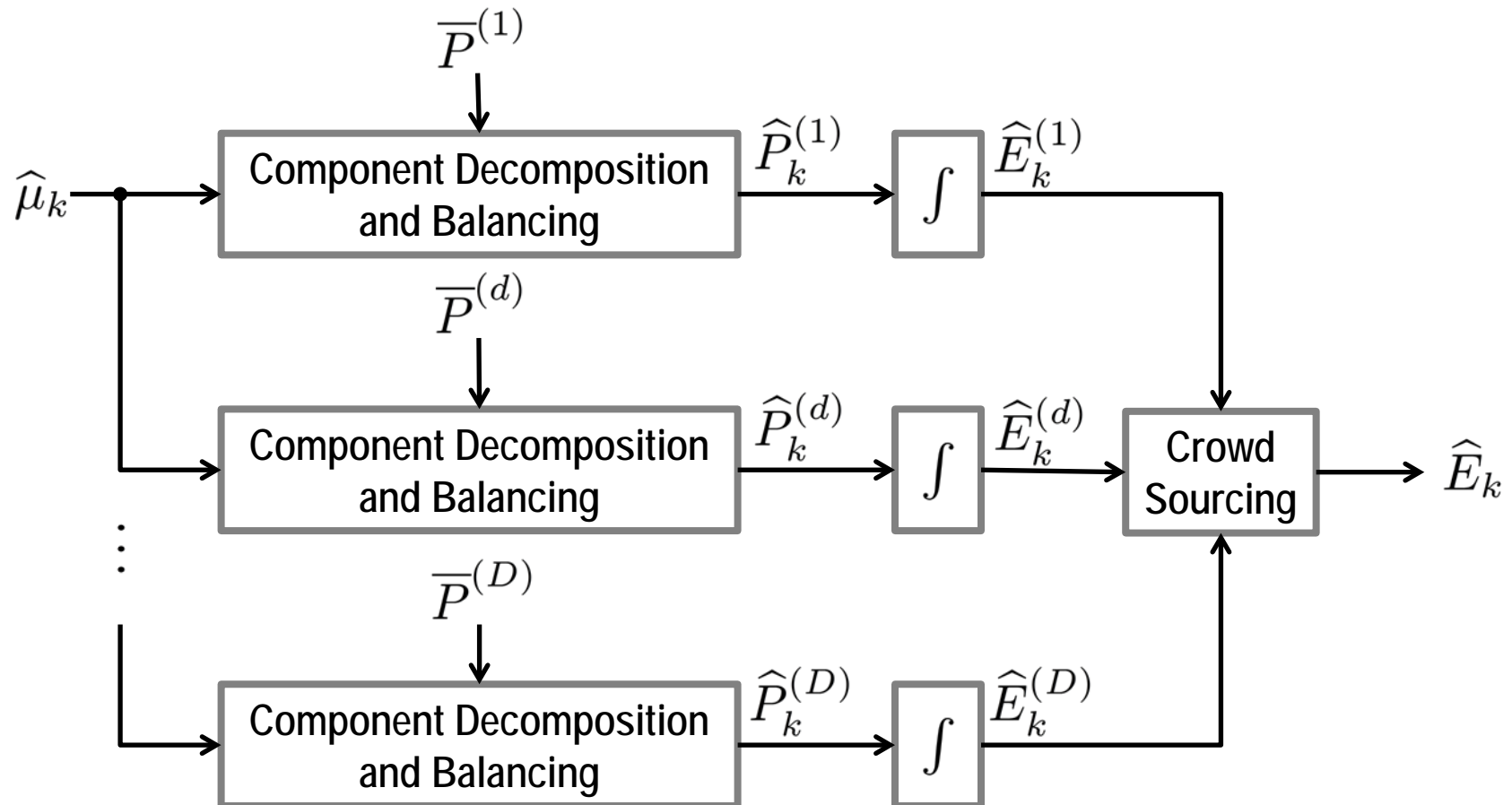


Crowdsourcing Power Ranges



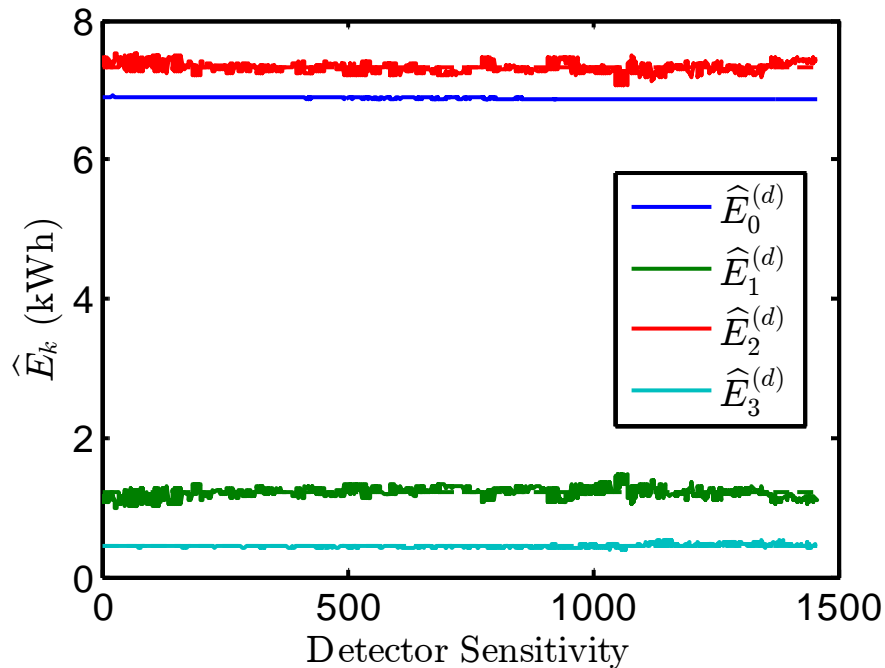
- 1,456 different power ranges
- Choose most frequent mode for each range for $\hat{\mu}_k$

Crowdsourcing Energy Estimates

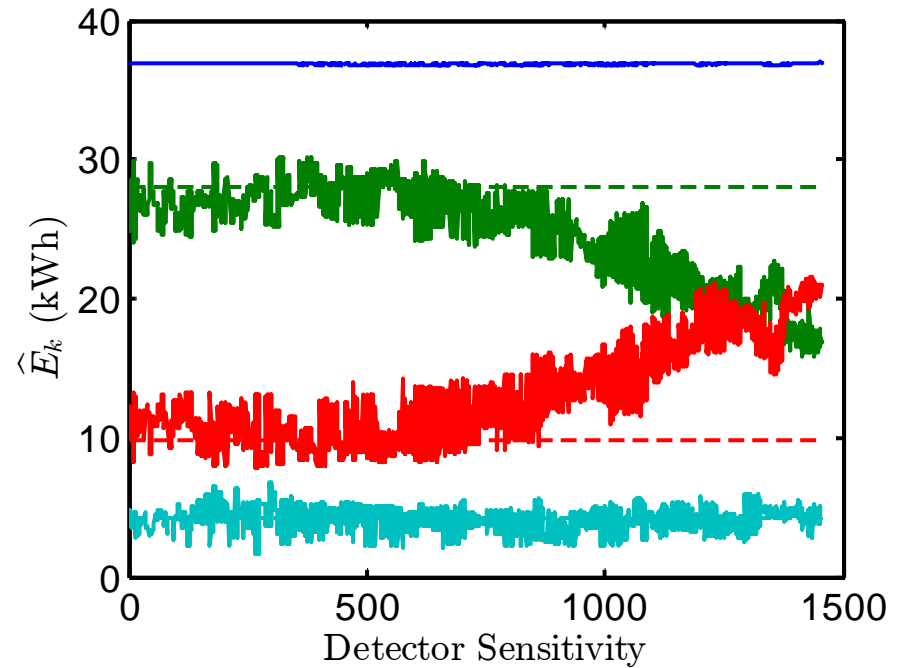


Crowdsourcing Energy Estimates

Phase A



Phase B



- 1,456 different energy estimates
- Crowdsourcing algorithm to find most stable region across all power consumption classes
- Energy estimate robust to event detection errors

Power Consumption Clustered-NILM

- PCC-NILM
 - Relaxation of full disaggregation problem
- Disaggregate according to power consumption ranges
 - Power ranges inferred from data
- Completely Unsupervised
- Approximate P and decompose into relevant components

$$P \approx \bar{P} = \bar{P}_0 + \sum_{k=1}^K \bar{P}_k$$

↑ Background and ↑ Active
 Components

- Energy obtained by integrating components

$$\bar{E}_k = \int \bar{P}_k dt$$

Future Work

- **Incorporate reactive power (Q)**
 - 2-D APTDA
- **Methods for selecting K**
 - Number of classes used for clustering
- **Single device classes**
 - Higher consumption devices have good separation
- **Sampling frequency analysis**
 - Used 1 Hz power data, can we do less?
- **Human computer interaction**
 - Study how to report information to use
- **Changing power range distributions**
 - Power ranges vary with consumption changes

Questions?