Non-Intrusive Load Monitoring: A Power Consumption Based Relaxation

Kyle D. Anderson, José M.F. Moura, and Mario Bergès

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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

NILM Background

- **Traditional event-based NILM framework**

  ![NILM Diagram]

- **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

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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]

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

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 $\mu_k$

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

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

<table>
<thead>
<tr>
<th>$k$</th>
<th>$\mu_k$</th>
<th>Power Consumption Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-</td>
<td>Background</td>
</tr>
<tr>
<td>1</td>
<td>69.2 W</td>
<td>0–105 W</td>
</tr>
<tr>
<td>2</td>
<td>140.8 W</td>
<td>105–720 W</td>
</tr>
<tr>
<td>3</td>
<td>1300.8 W</td>
<td>720+ W</td>
</tr>
</tbody>
</table>
PCC-NILM Solution Example

\[ \overline{P} = \overline{P}_0 + \sum_{k=1}^{K} \overline{P}_k \]
Approximate Power Trace Decomposition Algorithm (APTDA)
Power Trace Approximation

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

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

$$E_P = \int P \, dt = \int \overline{P} \, dt = E_{\overline{P}}$$
Approximate Power Trace Decomposition Algorithm (APTDA)

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

1. Event Detection
2. Power Trace Approximation
3. \( \Delta \bar{P} \) Clustering
4. \( \mu_k \)

\[
P \xrightarrow{\text{Event Detection}} e^{(1)} \xrightarrow{\text{Power Trace Approximation}} \bar{P}^{(1)} \xrightarrow{\Delta \bar{P}} \mu_k^{(1)} \xrightarrow{\text{Clustering}} P \xrightarrow{\text{Crowd Sourcing}} \hat{\mu}_k
\]
Crowdsourcing Power Ranges

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

\[ \hat{E}_k \]

\[ \hat{P}_k \]

\[ \int \]

\[ \hat{P}^{(1)}_k \]

\[ \hat{E}^{(1)}_k \]

\[ \hat{P}^{(d)}_k \]

\[ \hat{E}^{(d)}_k \]

\[ \hat{P}^{(D)}_k \]

\[ \hat{E}^{(D)}_k \]

Component Decomposition and Balancing

Component Decomposition and Balancing

Component Decomposition and Balancing

\[ \hat{\mu}_k \]
Crowdsourcing Energy Estimates

- 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**

\[
P \approx \overline{P} = \overline{P}_0 + \sum_{k=1}^{K} \overline{P}_k
\]

**Background and Active Components**

- **Energy obtained by integrating components**

\[
\overline{E}_k = \int \overline{P}_k \, dt
\]
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?