NILM 2016 Lightning Talks

Technical Program Committee

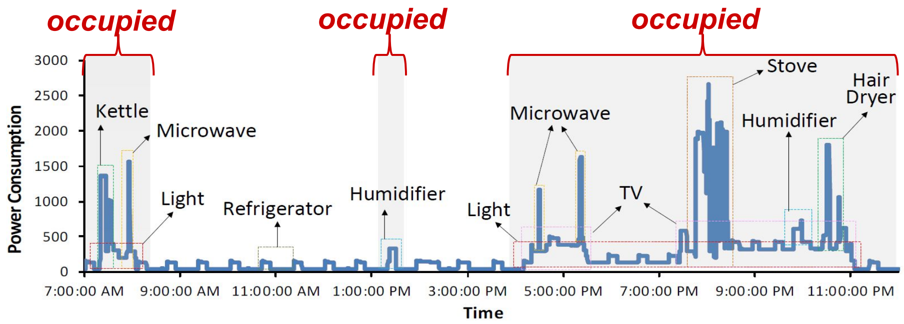
Sean Barker, Bowdoin College
Md. Zulfiquar Ali Bhotto, Simon Fraser University
Nipun Batra, IIIT Delhi
Mario Berges, Carnegie Mellon University
Kyle Bradbury, Duke University
Hsueh-Hsien Chang, Jin-Wen University of Science and Technology
Bradley Ellert, Simon Fraser University
Jingkun Gao, Carnegie Mellon University
Manoj Gulati, IIIT Delhi
Sidhant Gupta, Microsoft Research
Zhenyu Guo, Sengled
Milan Jain, IIIT Delhi
Jack Kelly, Imperial College
Alex Leontitsis, British Gas Connected Home
Jing Liao, University of Strathclyde
Wenpeng Luan, China EPRI
Lucas Pereira, Madeira-ITI
Alex Rogers, University of Oxford
Karim Said Barsim, Universitat Stuttgart
Shima Shojae, University of British Columbia
Guoming Tang, University of Victoria
Akshay Uttama Nambi, TUDelft
Mingjun Zhong, University of Edinburgh

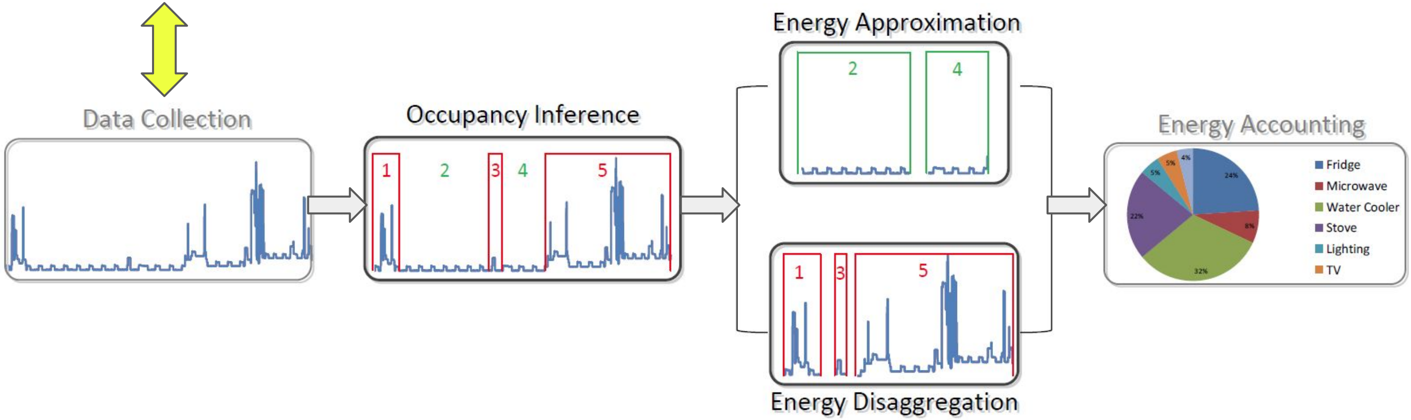
Running order

1. Occupancy-aided Energy Disaggregation
2. Analyzing 100 Billion Measurements: A NILM Architecture for Production Environments
3. An Accurate Method of Energy Use Prediction for Systems with Known Composition
4. Simple Event Detection and Disaggregation Approach for Residential Energy Estimation
5. Towards a Cost-Effective High-Frequency Energy Data Acquisition System for Electric Appliances
6. Unsupervised Learning Algorithm using multiple Electrical Low and High Frequency Features for the task of Load Disaggregation
7. WHITED - A Worldwide Household and Industry Transient Energy Data Set
8. Event Detection in NILM using Cepstrum smoothing
9. A New Measurement System for High Frequency NILM with Controlled Aggregation Scenarios
10. Graphical Closure Rules for Unsupervised Load Classification in NILM Systems
11. An Improved Event Detection Algorithm for Non-Intrusive Load Monitoring System for Low Frequency Smart Meters

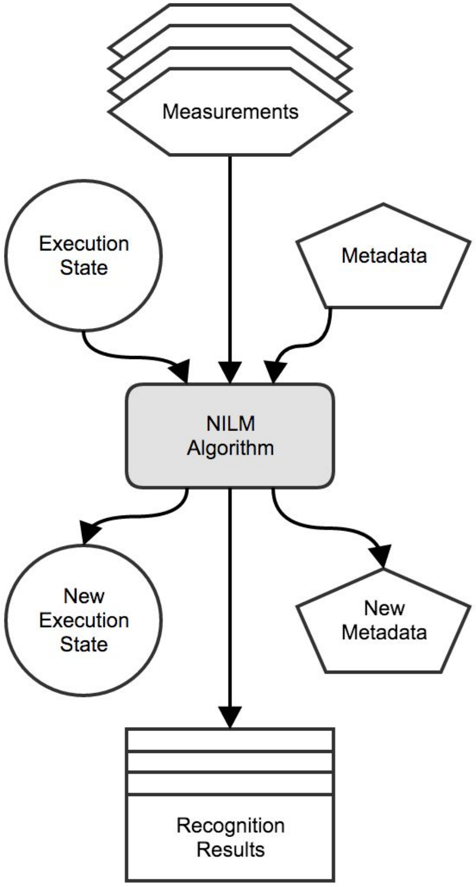
Occupancy-aided Energy Disaggregation

— to reduce *computational complexity*



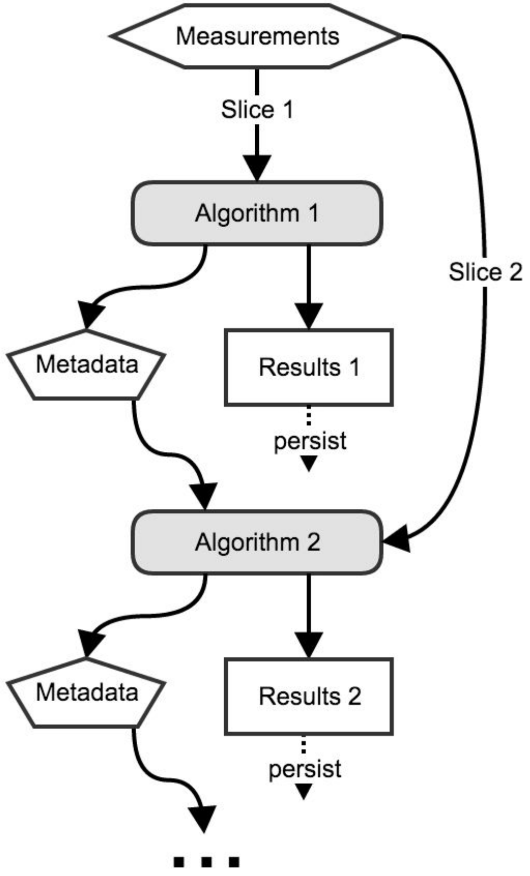


Guoming Tang and *Kui Wu*, **University of Victoria, BC, Canada**



One interface ...

... many NILM approaches



An accurate method of energy use prediction for systems with known composition

Jacob A. Mueller and Jonathan W. Kimball, Missouri University of Science and Technology

Distinguishing Assumption

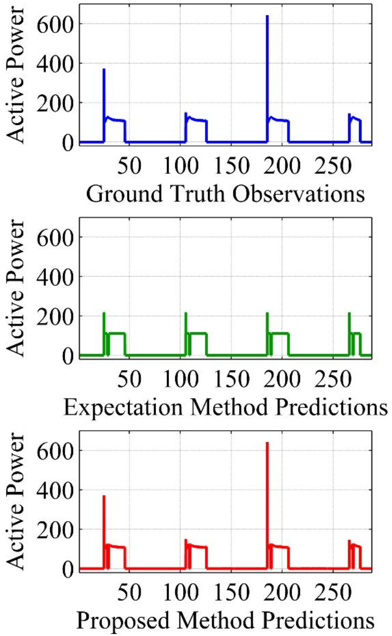
- System contains no unmodeled devices
- Valid for industrial and vehicular power systems, not for residential applications

Key Approach

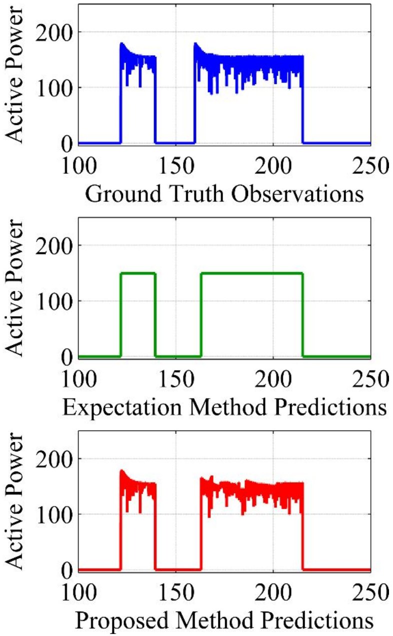
- Maximize probability of device-level predictions as a constrained optimization problem
- Resulting predictions provide time-accurate profiles of device behavior

Applications

- Early warning of device damage or malfunction
- Noninvasive support for fault detection, identification, and recovery operations



Comparison of Refrigerator Results



Comparison of LCD TV Results

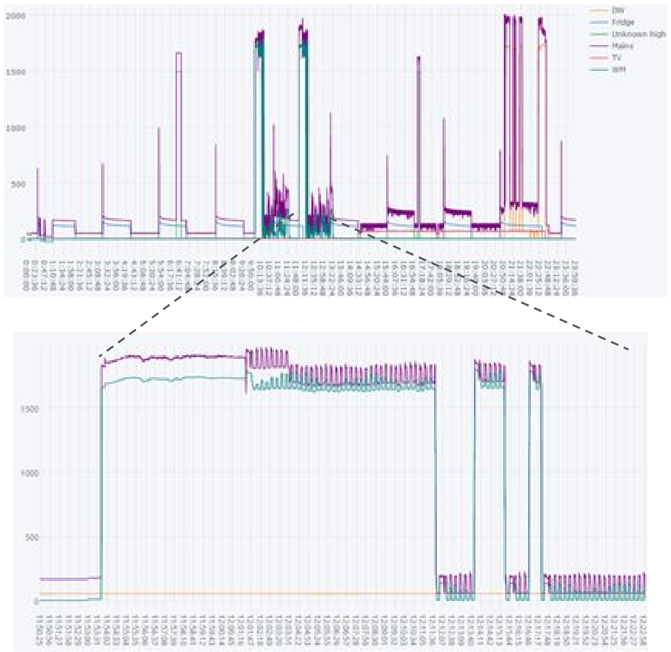
POLITECNICO DI TORINO

Simple Event Detection and Disaggregation Approach for Residential Energy Estimation

Awet A. Girmay, Christian Camarda

•Signal acquisition using ned-meter, Flex-plug & data from big utility suppliers in Italy.

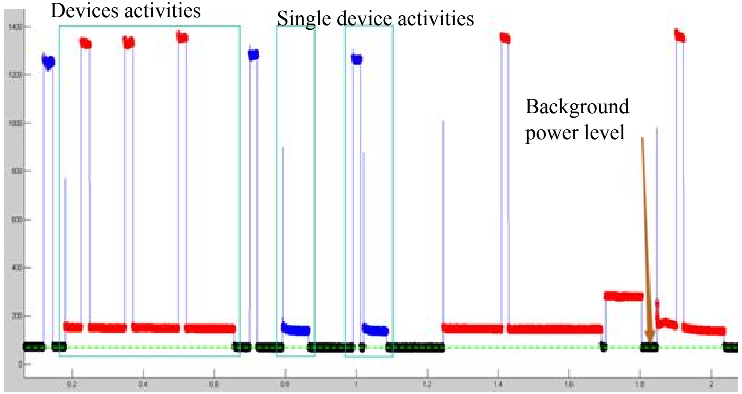
•Associate paired events to appliances based on geometric spike features and usage patterns of loads.



•An active window based NILM approach for event detection and feature extraction.

•Utilizes an unsupervised localized events clustering and pairs matching using automatic clustering methods (DE & GA)

•Identifies active windows as single or multiple devices operations and learns power states observed.

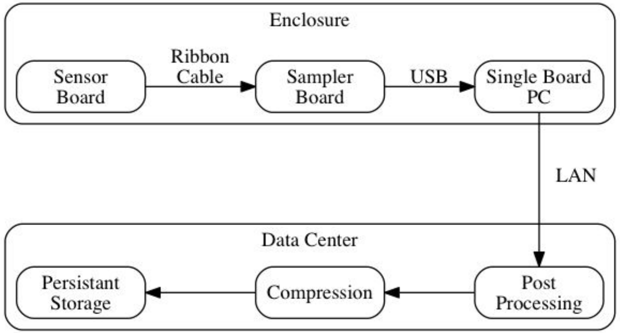


www.midorisrl.eu

Towards a Cost-Effective High-Frequency Energy Data Acquisition System for Electric Appliances

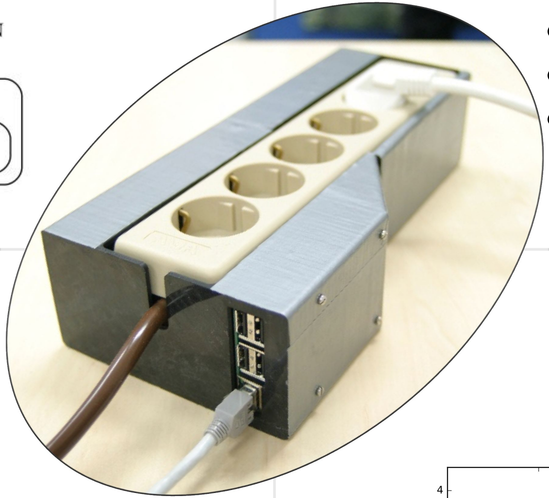
Thomas Kriechbaumer, Anwar Ul Haq, Matthias Kahl, and Hans-Arno Jacobsen

Technical University of Munich



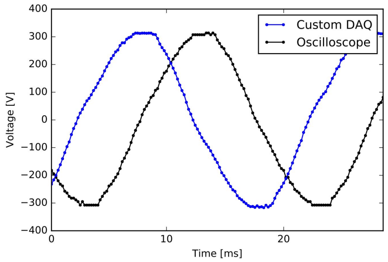
Features

- Modular design
- Waveform reconstruction
- Fully independent monitored power outlets
- Configurable sampling frequency: up to 30 kHz
- Cost-effective data acquisition: less than 100€



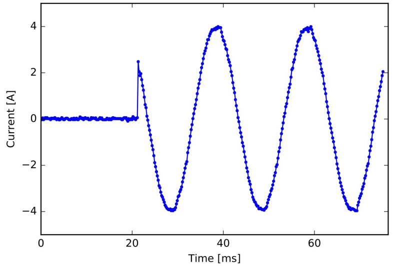
Sensor Board

- Power supply: 5V @ 1W
- Current signals: 6 independent ACS712
- Voltage signal: 6Vrms AC-AC transformer



Sampler Board

- Attached to Raspberry Pi via GPIO and USB
- Independent 12-bit ADCs: MCP3201
- Microcontroller : ATmega324PA
- USB interface: FTDI232H



Unsupervised Learning Algorithm using multiple Electrical Low and High Frequency Features

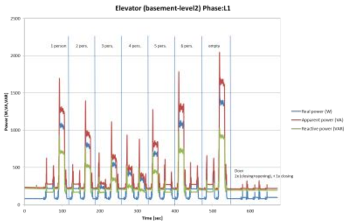
Supported by:

Federal Ministry
for Economic Affairs
and Energy

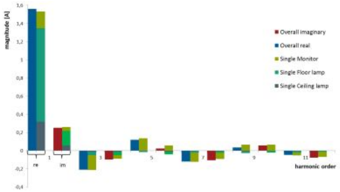
on the basis of a decision
by the German Bundestag

Electrical Features

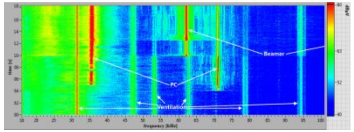
a. Real and reactive power



b. Harmonics

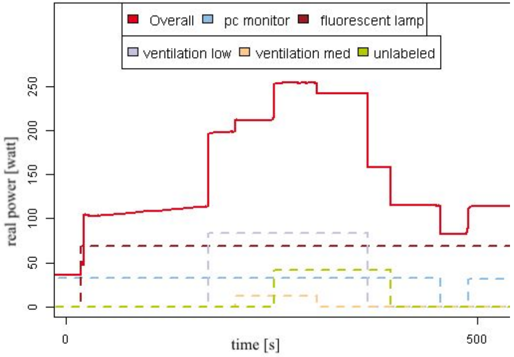


c. EMI



Unsupervised Learning

- Event-based & clustering approach
- New project in industrial applications



NILM
NONINTRUSIVE
LOAD MONITORING

Fraunhofer
IMS

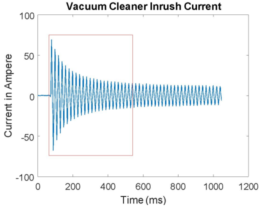
WHITED A Worldwide Household and Industry Transient Energy Data Set

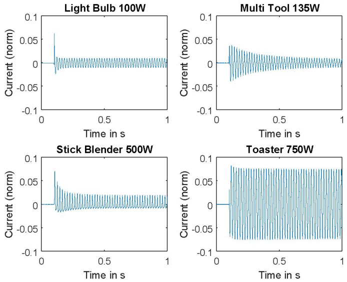
Matthias Kahl, Anwar Ul Haq, Thomas Kriechbaumer, Hans-Arno Jacobsen

Technical University of Munich

Motivation

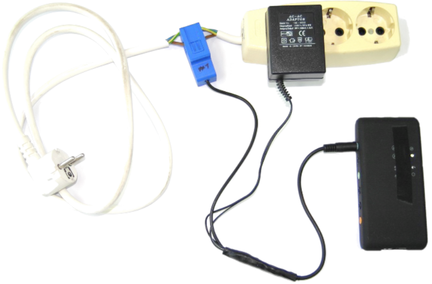
- High resolution data
- Simple design
- Low cost components
- Crowd sourced initiative





Data Set Facts

- Sampling with 44.100Hz @ 16-Bit
- 10 start-ups for each appliance
- 1100 different records as flac files
- 110 different appliances
- 47 different appliance types
- Data from 7 regions / 3 countries



Measurement Equipment

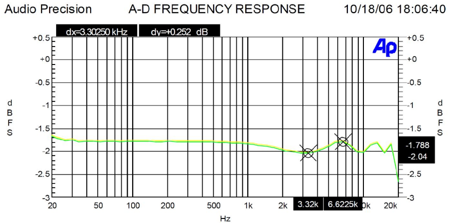
For measuring the current, we use a

- 3-port extension cord
- YHDC current clamp (30A/1V)
- AC-AC transformer (230V to 11V)
- Voltage divider (11V to 0.47V)
- CSL USB sound card (CM6206 Chipset)

Drilling machine
Pro Work SMJ 500e

Toaster
Powertec

Mixer
Kenwood CH580



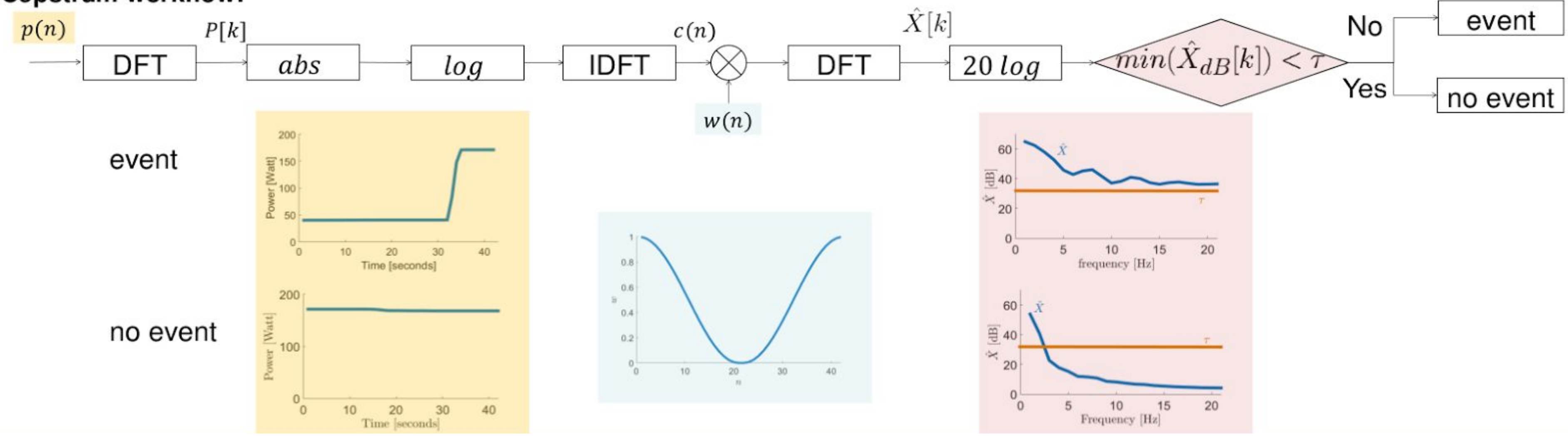
Data Quality

- Spectral nonlinearity < 0.26dB at 3320Hz
- Sound card line-in SNR: ~76dB
- Current / power step size: 13.5 mA / 3.1 W

Event Detection in NILM using Cepstrum smoothing

Leen De Baets, Joeri Ruyssinck, Dirk Deschrijver and Tom Dhaene, Ghent University

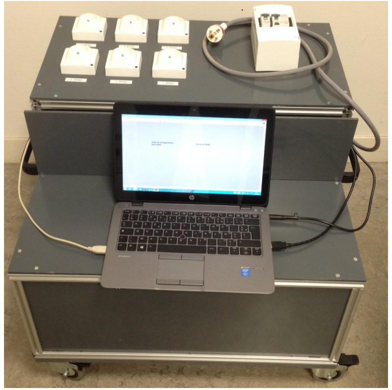
Cepstrum workflow:



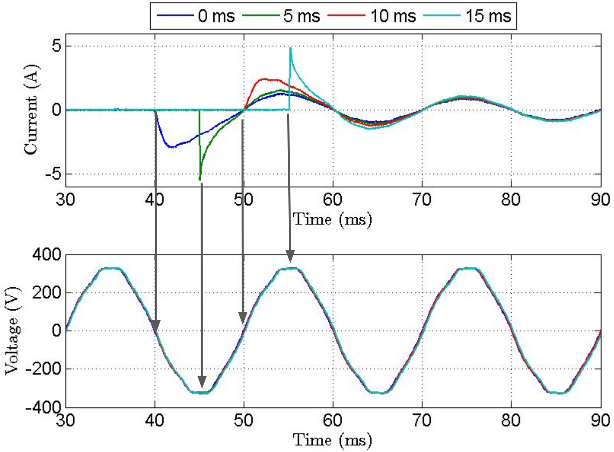
UNIVERSITEIT GENT
iMinds
INTEC

A New Measurement System for High Frequency NILM with Controlled Aggregation Scenarios

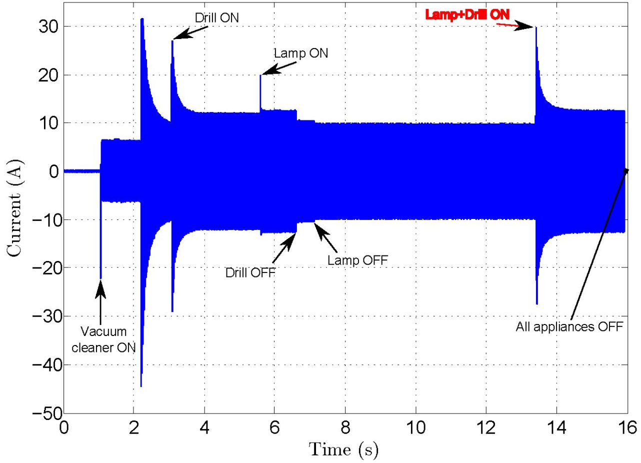
Mohamed Nait Meziane, Thomas Picon et al., *University of Orléans, France*



A variable sampling rate up to 1.25 MHz



The control over turn-on/off wrt the AC sinusoid



Aggregation scenarios (up to 6 loads)

PRISME
Laboratoire Pluridisciplinaire de Recherche Ingénierie des Systèmes, Mécanique, Énergétique

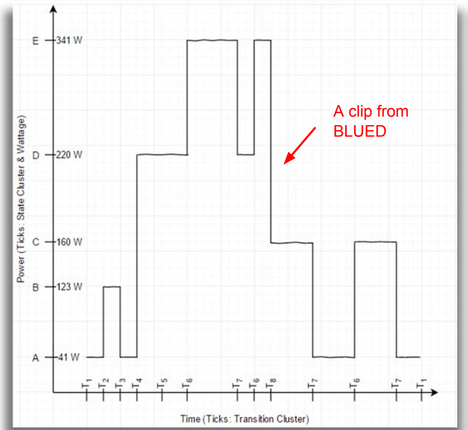
UNIVERSITE D'ORLEANS

Graphical Closure Rules for Unsupervised Load Classification in NILM Systems

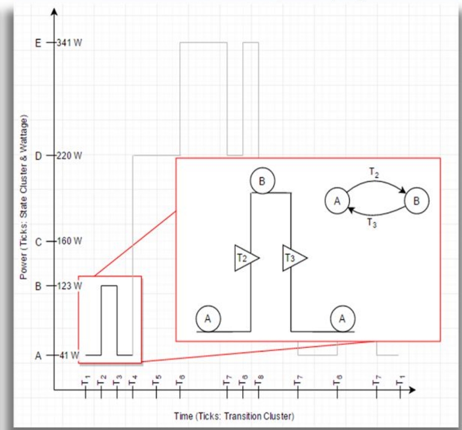
Joseph Krall, Sohei Okamoto, Hampden Kuhns

1) Event Detection: steady states and transitions. Clustering: fixed-Radius, nearest neighbor.
2) Graph: Steady States are vertices. Transitions are edges.
3) Cycle detection: transitions in cycles become closure rules.
4) 1x1 rule/cycles (+x, -x) represent loads. Transitions are defined.
5) Graph traversal from min-power steady state. Steady states are defined.

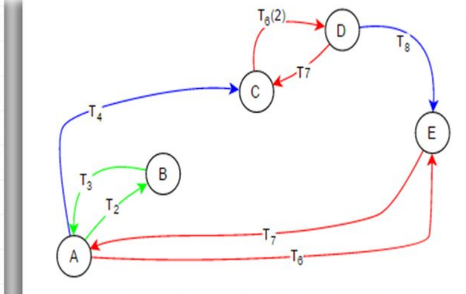
Initial Data (1)



Build a Graph (2)

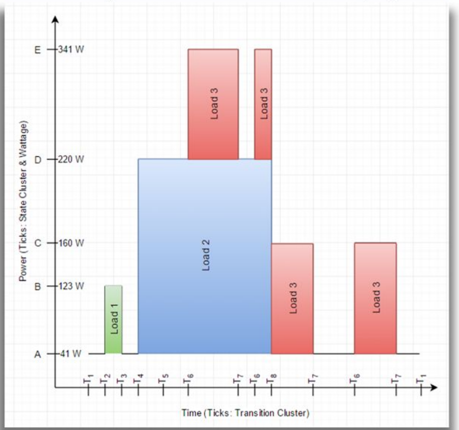


Closure Rules (3,4)



Cycles:	Closure Rules:	Simplified Closure Rules:	Loads:
AB	T_2-T_3	T_2-T_3	L_1
CD	T_6-T_7	T_6-T_7	L_2
AE	T_6-T_7		
ACD	T_4-T_6-T_8-T_7	T_4-T_8	L_3

Map Loads to Data (5)



LoadIQ 800 Haskell Street
Reno, NV, USA

LoadIQ is a company based in Reno, NV, which provides energy monitoring solutions to its clients. For more information regarding LoadIQ, please visit www.loadiq.com

An Improved Event Detection Algorithm for Non-Intrusive Load Monitoring System for Low Frequency Smart Meters

Abdullah Al Imran, Minhaz Ahmed Syrus, and Hafiz Abdur Rahman

Windowing sampling and steady-state averaging causes edge offset.

- Use two threshold edge detection algorithm to detect consistent edge, reduce edge/event offset
- Real power edge and reactive power edge matching, edge pruning
- Transient impulse/edge detection as a complementary parameter to differentiate event space overlaps

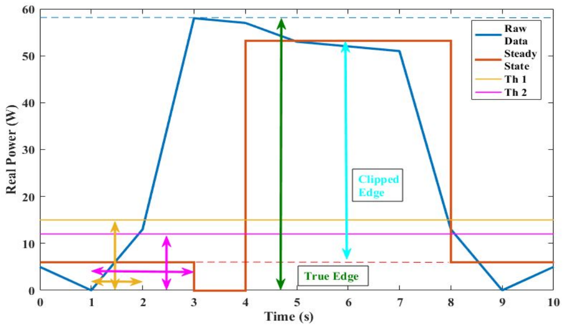


Fig.: Edge offset

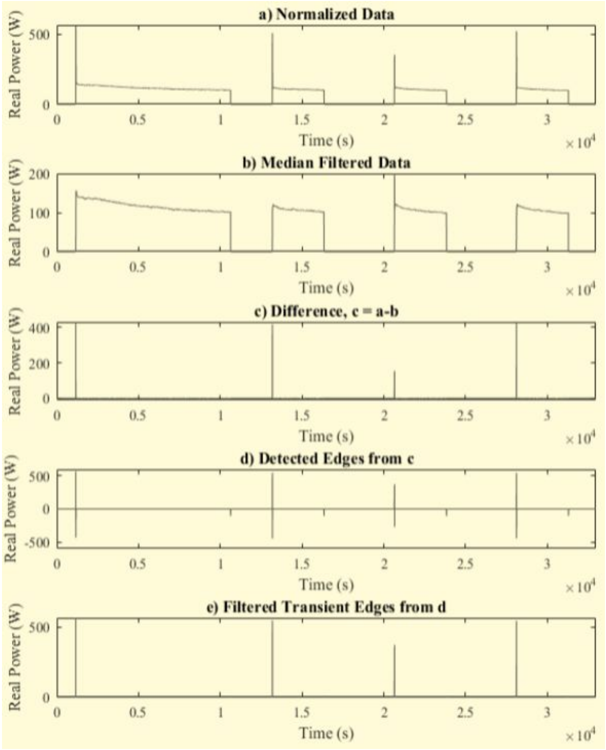


Fig.: Five Steps of Transient edge detection

Fig.: Edge offset (iAWE data)

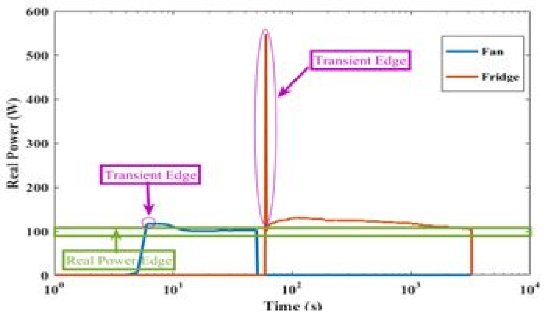


Fig.: Transient edge as a differentiating parameter