A New Unsupervised Event Detector for Non-Intrusive Load Monitoring

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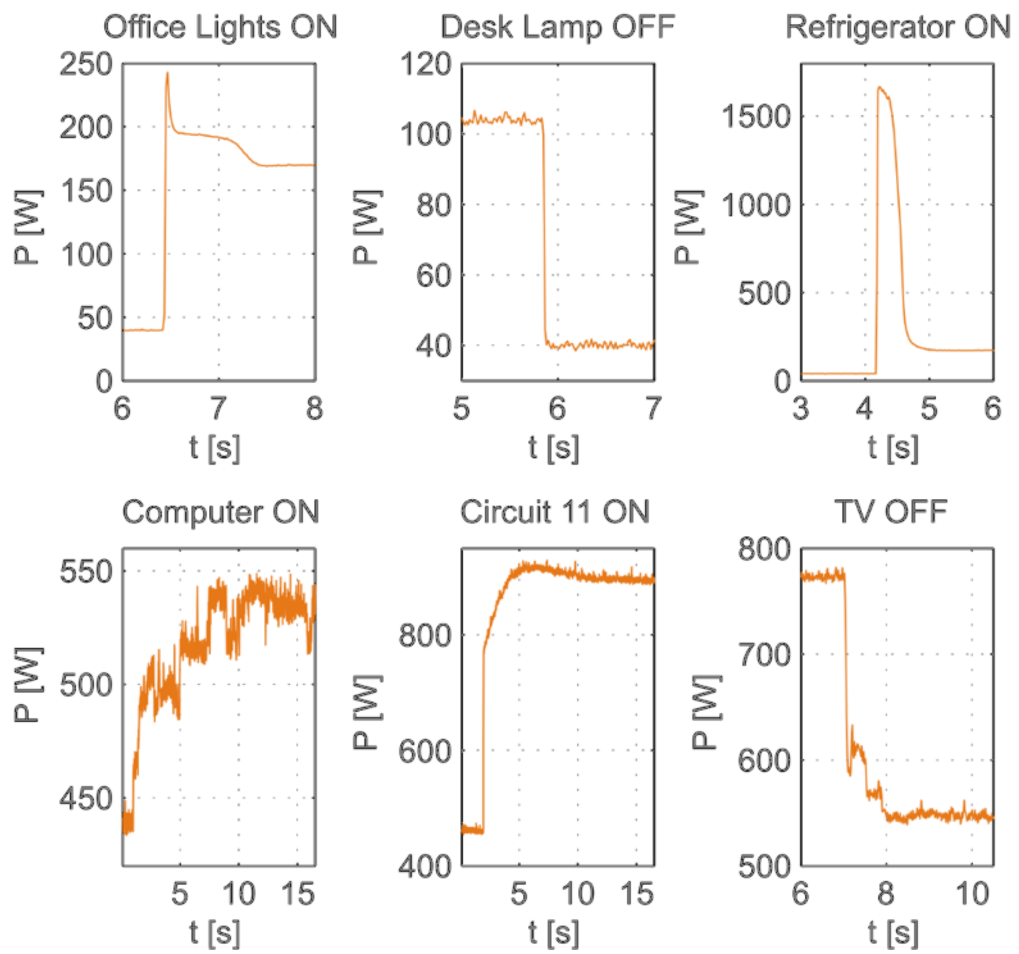
Introduction

- Change interval detection in aggregate NILM signals.

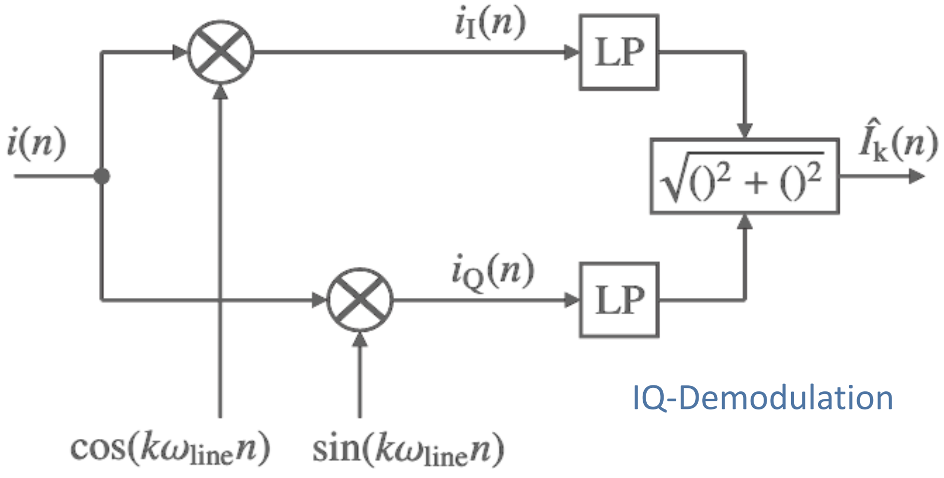
- Motivations:
  - Reliable transient feature extraction.
  - Noise-free space for unsupervised and semi-supervised event-based NILM.



[1] K. Anderson, A. Ocneanu, D. Benitez, D. Carlson, A. Rowe, and M. Berges, "BLUED: a fully labeled public dataset for Event-Based Non-Intrusive load monitoring research," in Proceedings of the 2nd KDD Workshop on Data Mining Applications in Sustainability (SustKDD), Beijing, China, Aug. 2012

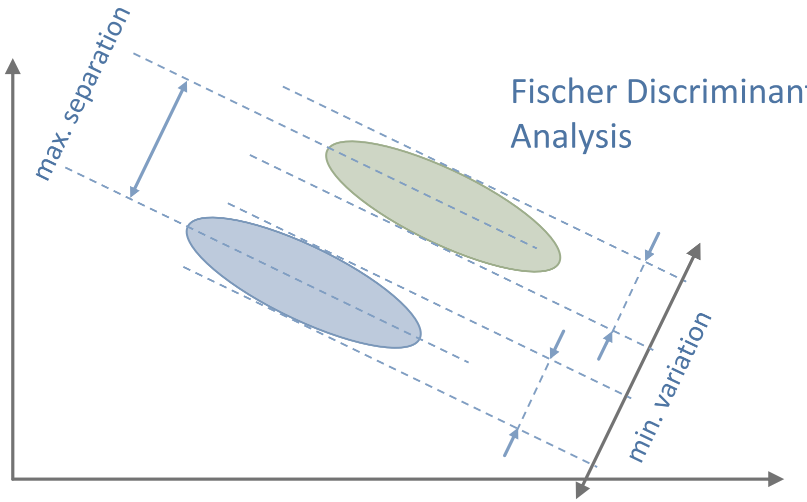
Task and tools

- Task:
  - Real-time harmonic analysis of aggregate current signals.
  - Accurate segmentation of aggregate NILM signals.
  - Addressing time varying loads in event-based NILM.
  - Change detection in harmonic components.
  - High detection sensitivity and more robustness to noise.
  - High dimensional aggregate signals (harmonics).



IQ-Demodulation

- Tools:
  - Harmonic analysis: ***IQ-Demodulation***
  - Event detection: ***Kernel Fischer Discriminant Analysis (KFDA)***[1]



Fischer Discriminant Analysis

- NILM test dataset: ***BLUED***[2]
  - Suitable for event-based energy disaggregation

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[1] S. Mika, A. J. Smola and B. Schoelkopf, "An improved training algorithm for kernel Fisher discriminants", Proc. AISTATS, pp. 98–104, 2001.

[2] K. Anderson, A. Ocneanu, D. Benitez, D. Carlson, A. Rowe, and M. Berges, "BLUED: a fully labeled public dataset for Event-Based Non-Intrusive load monitoring research," in Proceedings of the 2nd KDD Workshop on Data Mining Applications in Sustainability (SustKDD), Beijing, China, Aug. 2012

Harmonic analysis

- Instantaneous current $i(n)$ and voltage $v(n)$ signals

$$v(n) = \sqrt{2}\sum_{k=1}^{H} V_k(n)\cos(\,k\,\omega_1(n)\,n + \varphi_k^V)$$

$$i(n) = \sqrt{2}\sum_{k=1}^{H} I_k(n)\cos(\,k\,\omega_1(n)\,n + \varphi_k^I)$$

- Event detection on current harmonics
  - Changes in higher harmonics may not be observed in the aggregate power signals.

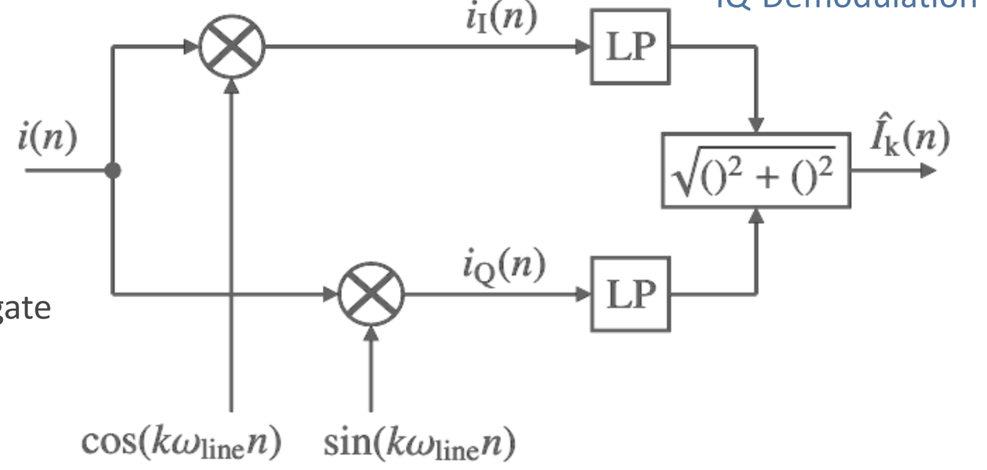
$$P = \frac{1}{T}\int_0^T v(n)i(n)dn = \sum_{k=1}^{H} V_k I_k \cos(\varphi_k^{IV})$$

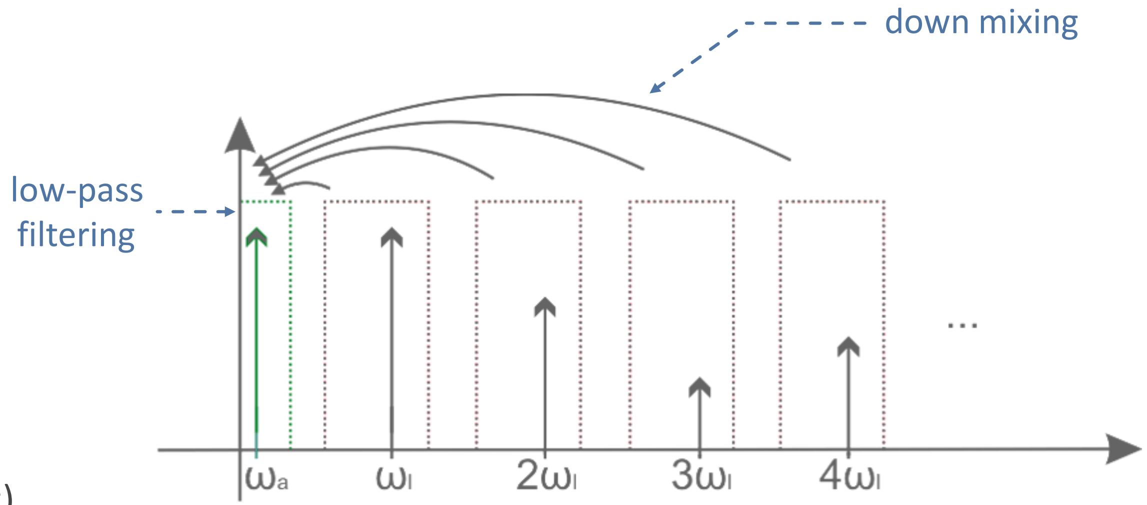
  - $V_k \sim 0$ for $k > 1$
- IQ-Demodulation (down-mixing)
  - In-phase: $i_I(n) = i(n)\cos(k\,\omega_{\text{line}} n)$
  - Quadrature: $i_Q(n) = i(n)\sin(k\,\omega_{\text{line}} n)$
- Low-pass filtering:
  - Narrow frequency band around each component.
- Harmonics components:

$$\hat{I}_k(n) = \sqrt{LP\big(i_I(n)\big)^2 + LP\big(i_Q(n)\big)^2}$$

- Robust to variations in the grid line frequency (50 or 60 Hz).

IQ-Demodulation





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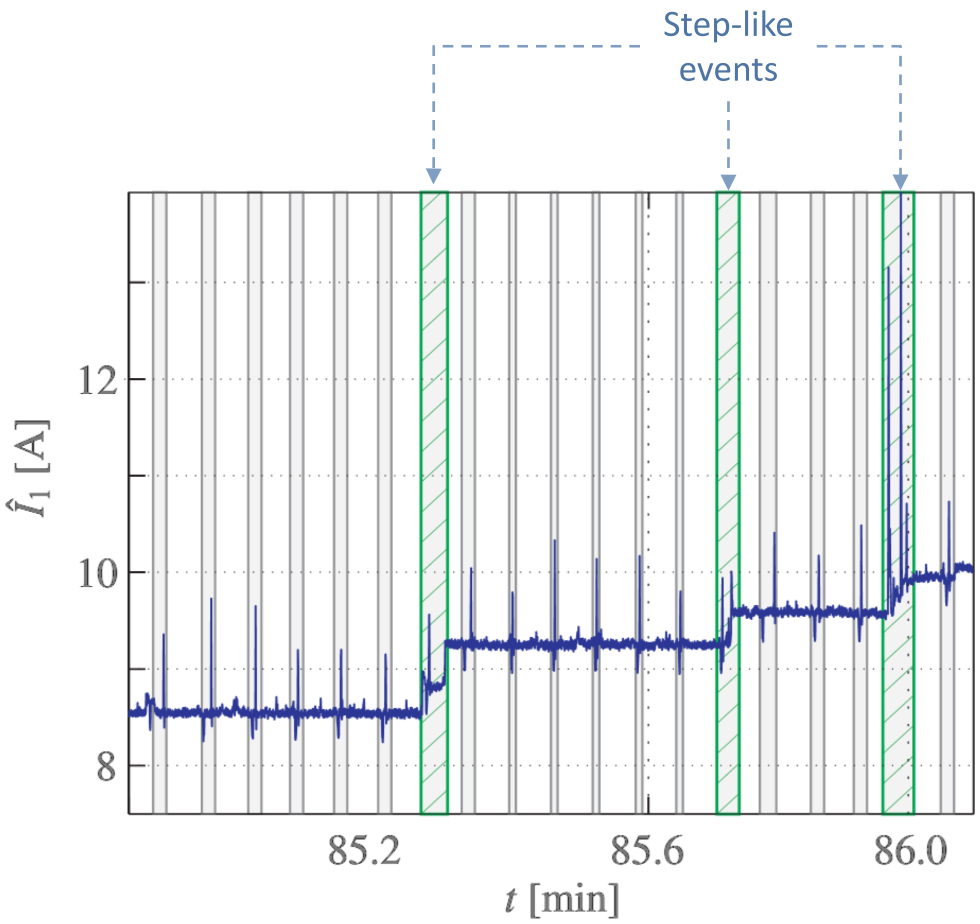
Event detection 1: problem definition

- Input signals: current harmonics

$$\underline{\theta}(n) = [\hat{I}_1, \hat{I}_3, \dots, \hat{I}_H]$$

  - The first 11 (odd) harmonic components

- Step-like change:
  - a change from one steady state to another.
  - mainly suitable for on-off and FSM loads.
- Active section:
  - a change in the signal from the current steady state.
  - includes intervals caused by time varying loads.
- The detection problem: *a binary test*
  - H_0: steady state (null)
  - H_1: active section (alternative)
  - Estimate $H \in \{H_0, H_1\}$



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Event detection 2: test statistic

- Principal Component Analysis (PCA):
  - Unsupervised dimensionality reduction.
  - Maximize intra-class variations.
  - Projection in the direction of the maximum variance.
- Kernel Fischer Discriminant Analysis (KFDA):
  - Supervised dimensionality reduction.
  - Maximize inter-class separation:

$$\mathbf{S}_B^{\phi} = \left(\underline{\mu}_2^{\phi} - \underline{\mu}_1^{\phi}\right)\left(\underline{\mu}_2^{\phi} - \underline{\mu}_1^{\phi}\right)^T$$

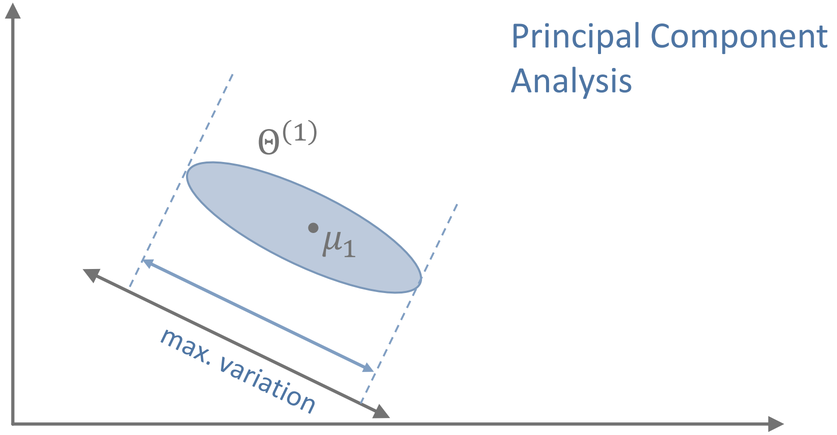
  - Minimize intra-class variation:

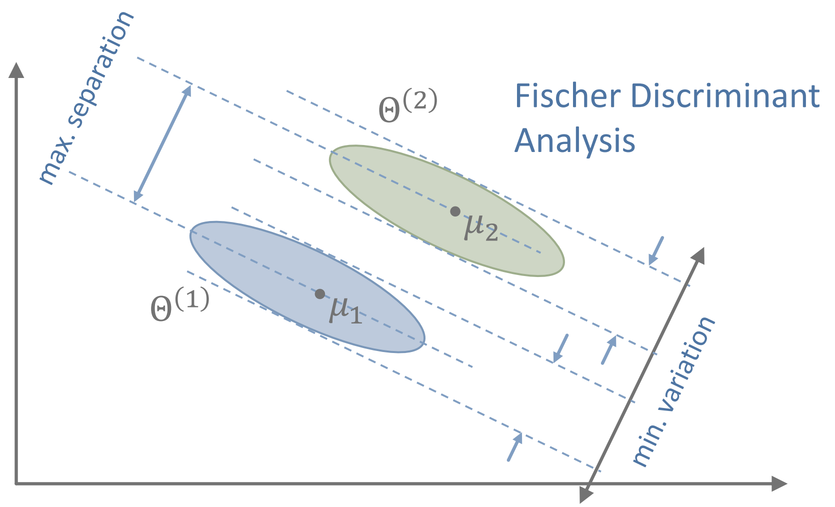
$$\mathbf{S}_W^{\phi} = \sum_{i=1,2} \sum_{\underline{\theta} \in \Theta^{(i)}} \left(\phi(\underline{\theta}) - \underline{\mu}_i^{\phi}\right)\left(\phi(\underline{\theta}) - \underline{\mu}_i^{\phi}\right)^T$$

  - Objective function:

$$\underline{v}^* = \arg\max_{\underline{v}} \left(J^{\phi}(\underline{v}) = \frac{\underline{v}^T \mathbf{S}_B^{\phi} \underline{v}}{\underline{v}^T \mathbf{S}_W^{\phi} \underline{v}} \right)$$

- The value of $J^{\phi}(\underline{v}^*)$ is a proximity measure between the two distributions and ϕ is the kernel function.





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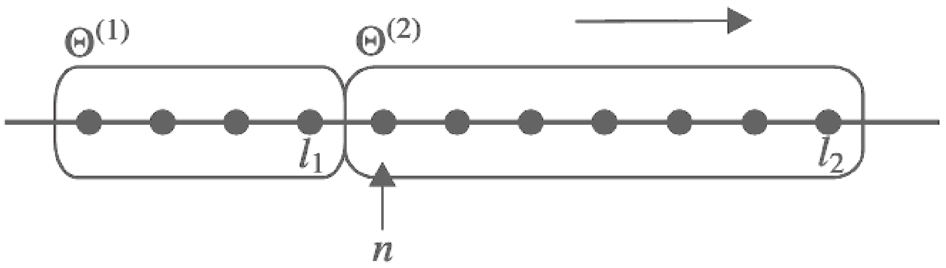
Event detection 2: test statistic

- A main sliding window consisting of two sub-windows:

$$\Theta^{(1)} = \{\underline{\theta}_1^{(1)}, \underline{\theta}_2^{(1)}, \dots, \underline{\theta}_{l_1}^{(1)}\}$$
$$\Theta^{(2)} = \{\underline{\theta}_1^{(2)}, \underline{\theta}_2^{(2)}, \dots, \underline{\theta}_{l_2}^{(2)}\}$$



- Fischer Discriminant Analysis[3]:

$$\underline{\nu}^* = \arg\max_{\nu} J^{\phi}(\underline{\nu}) = \left(\mathbf{S}_B^{\phi} + \gamma \mathbf{I}\right)^{-1} \left(\underline{\mu}_2^{\phi} - \underline{\mu}_1^{\phi}\right)$$

- Gaussian kernel function:

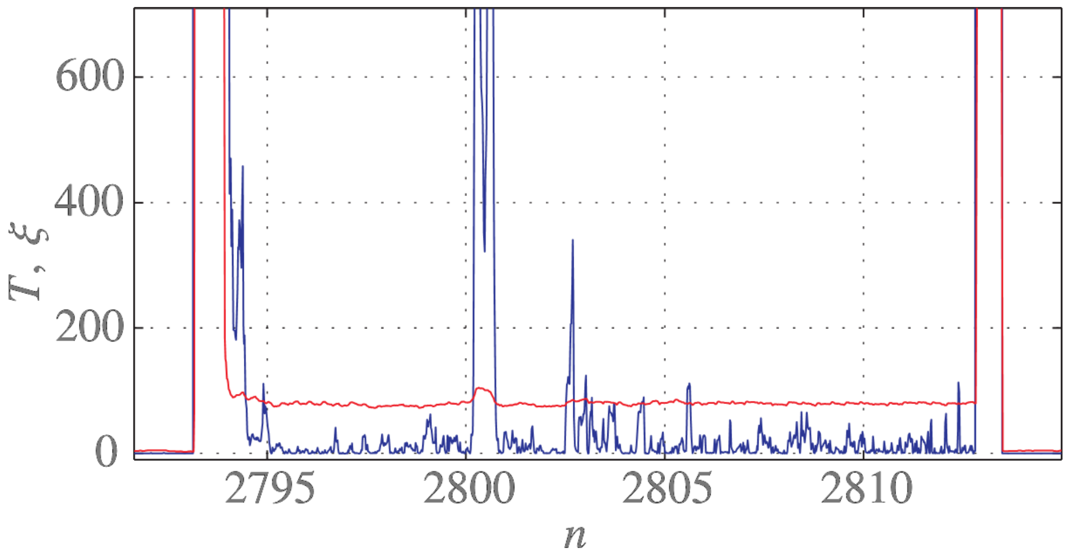
$$\phi\left(\underline{\theta}(i), \underline{\theta}(j)\right) = \exp\left(-\frac{\left\|\underline{\theta}(i) - \underline{\theta}(j)\right\|^2}{2\sigma^2}\right)$$

- Test statistic:

$$T = J^{\phi}\left(\underline{\nu}^*\right)$$

where

$$\hat{H} = H_0 \quad \text{if} \quad \mathrm{T} \le \xi$$
$$\hat{H} = H_1 \quad \text{otherwise}$$



- Dynamic threshold $\xi(n)$:

$$\xi(n) = \beta \sum_{i=1}^{H} \operatorname{std}\left(\hat{I}_i(n - l_1), \dots, \hat{I}_i(n + l_2 - 1)\right)$$

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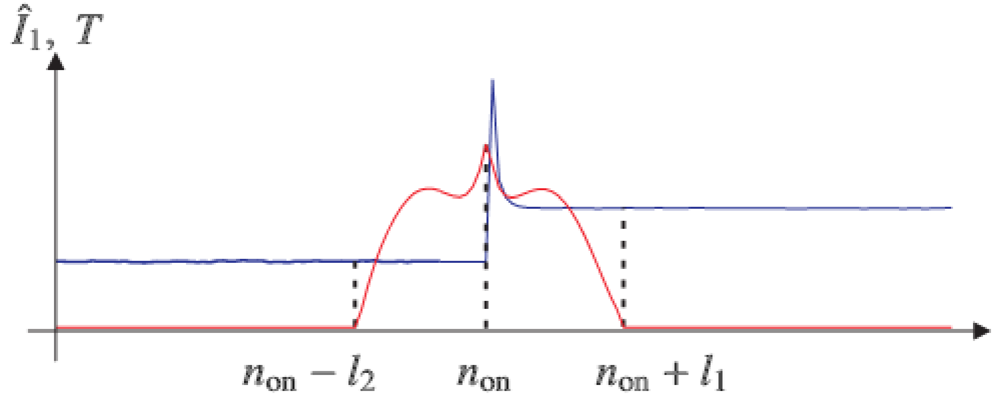
[3] Z. Harchaoui, F. Bach, O. Cappe and E. Moulines, “Kernel-based methods for hypothesis testing”, IEEE Signal Processing Magazine, pp. 87–97, 2013

Event detection 3: post processing

- Post-detection constraints:

$$n_{end,coarse} - n_{start,coarse} \geq l_1 + l_2$$

$$E_d = \sum_n T(n) - \xi(n) > \lambda$$

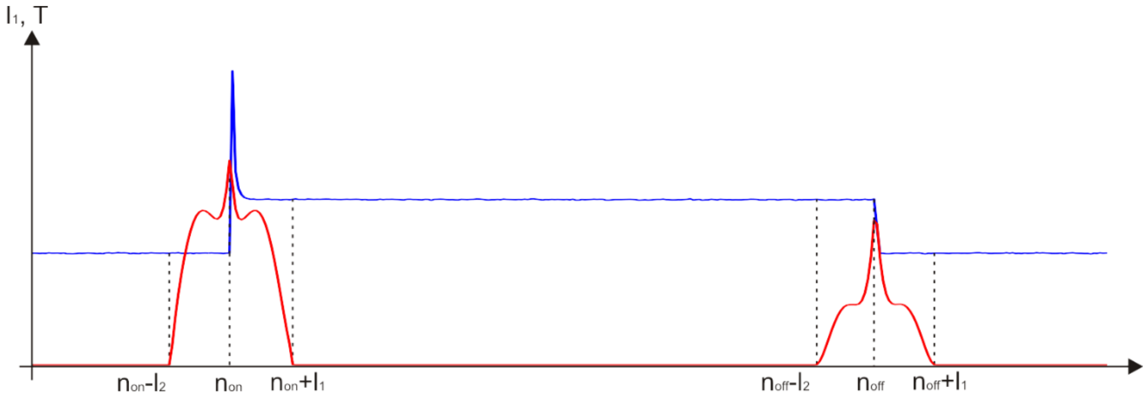


- Refinement:

$$n_{start,fine} = n_{start,coarse} + l_2$$

$$n_{end,fine} = n_{end,coarse} - l_1$$

- Step-like events:
  - Min. change in mean values.



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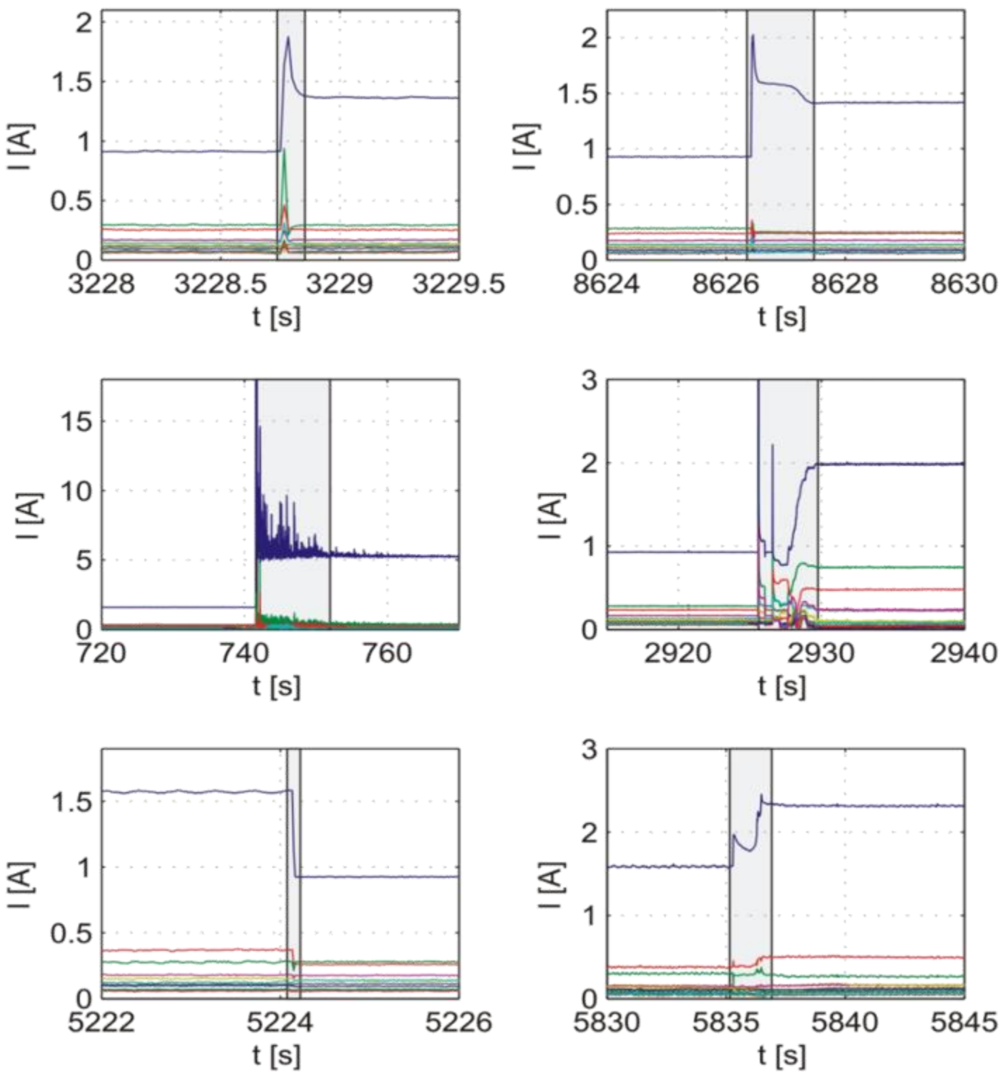
Experiment: BLUED

- **Test dataset:** BLUED[1]
  - Residential, building-level, 2-phase (A,B) power dataset
  - Raw data: current $i(n)$ and voltage $v(n)$ at 12kHz sampling.
- **Harmonic analysis:** IQ-Demodulation
  - First 11 (odd) harmonic components of the current signal.
  - 8^{th} order IIR low pass filter with $f_c = 6\text{Hz}$
- **Event detection**: Kernel Fischer Discriminant Analysis (KFDA).
  - **D**ynamic threshold $\xi(n)$**.**
  - Post processing (extract only step-like events).
  - Min. difference in real power (8W)



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Results

- **Evaluation metrics:**
  - False Positive Percentage (FPP) = $\frac{FP}{E}$
  - Precision = $\frac{\text{TP}}{\text{TP+FP}}$
  - Recall = $\frac{\text{TP}}{\text{TP+FN}}$
  - F_1-Score = $\frac{2\ \text{TP}}{2\ \text{TP+FP+FN}}$

	Phase A	Phase B
# Events	898	1609
# Detections	890	1718
True Positives	887	1483
False Positives	3	235
False Negatives	11	126
False Positive Percentage (FPP)	0.33%	14.61%
Precision	**99.66%**	**86.32%**
Recall	**98.78%**	**92.17%**
F1-score	**99.21%**	**89.15%**

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Discussion

Thank you
for your attention

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