



# Estimating Power Loads from Partial Appliance States

Nicolas Roux, Baptiste Vrigneau, Olivier Sentieys

## ► To cite this version:

Nicolas Roux, Baptiste Vrigneau, Olivier Sentieys. Estimating Power Loads from Partial Appliance States. NILM 2018 - 4th International Workshop on Non-Intrusive Load Monitoring, Mar 2018, Austin, United States. hal-01941877

**HAL Id: hal-01941877**

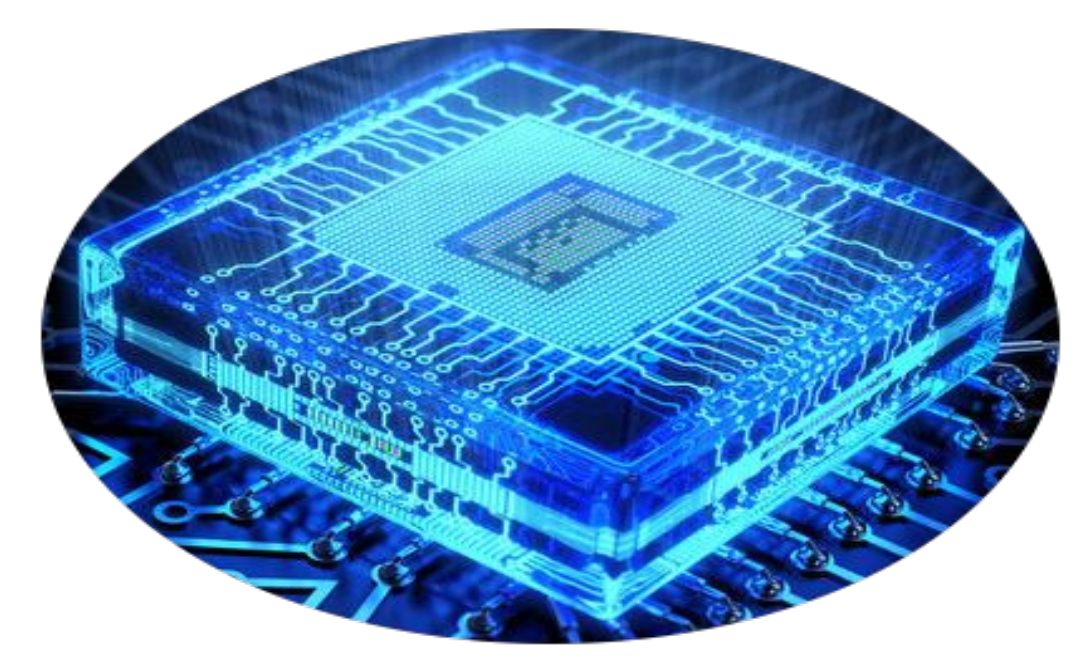
**<https://inria.hal.science/hal-01941877>**

Submitted on 10 Dec 2018

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.





# Estimating Power Loads from Partial Appliance States

Nicolas Roux (nicolas.roux@inria.fr), Baptiste Vrigneau, Olivier Sentieys

## General scope

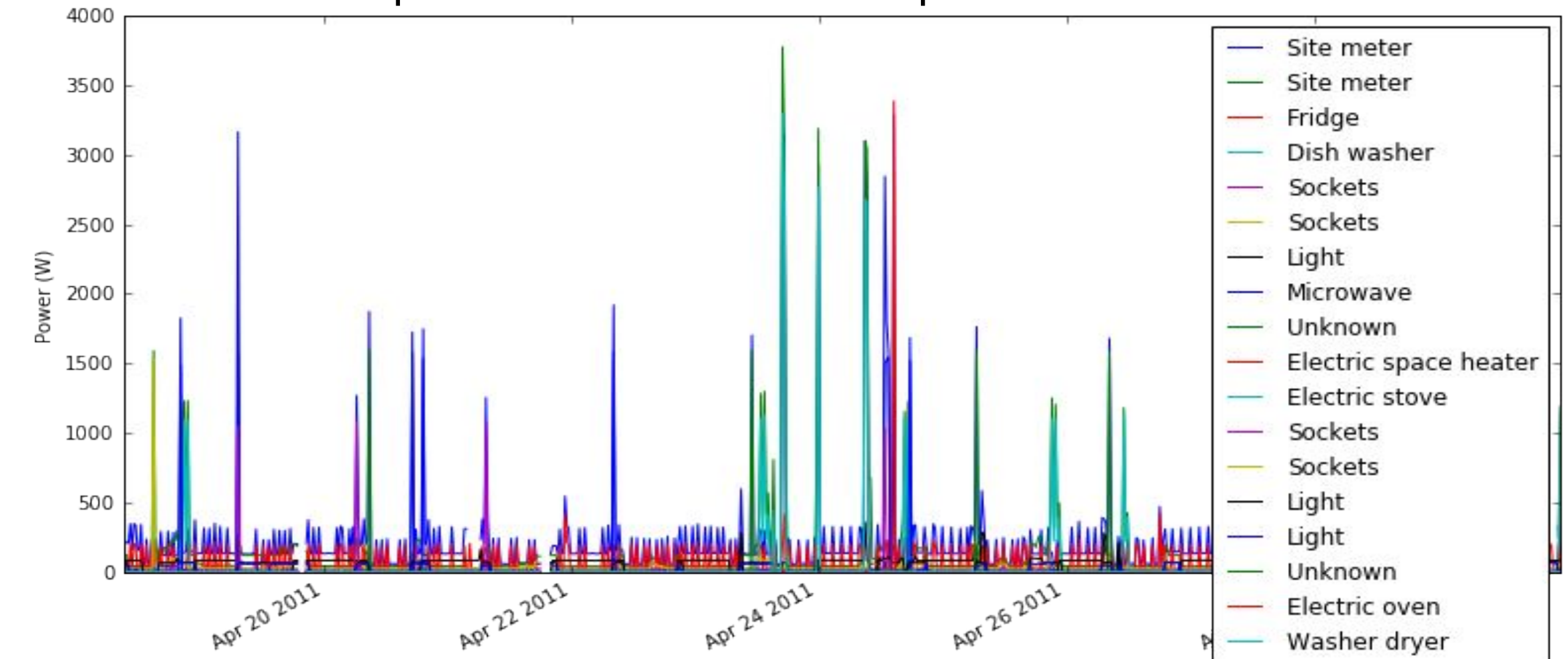
Knowing the plug-level power consumption of each appliance in a building can lead to significant savings in energy consumption, as well as giving a deep insight of a building power consumption. A critical information is the knowledge of the characteristic power consumptions of an appliance. The problem can be stated as an optimization problem as follows :

$$\min_{w_{i,j}} \|x_{tot}(t) - \sum_{i=1}^N \sum_{j=1}^{M_i} w_{i,j} \times s_{i,j}(t)\|_d \quad (1)$$

- $w_{i,j}$  the steady state power value  $j$  for appliance  $i$
- $x_{tot}$  the main aggregated power of all appliances
- $N$  the total number of monitored appliances
- $M_i$  the states count for appliance  $i$
- $s_{i,j}$  a boolean which indicates if appliance  $i$  is in state  $j$
- $d$  a given norm.

## Non-Intrusive Load Monitoring (NILM)

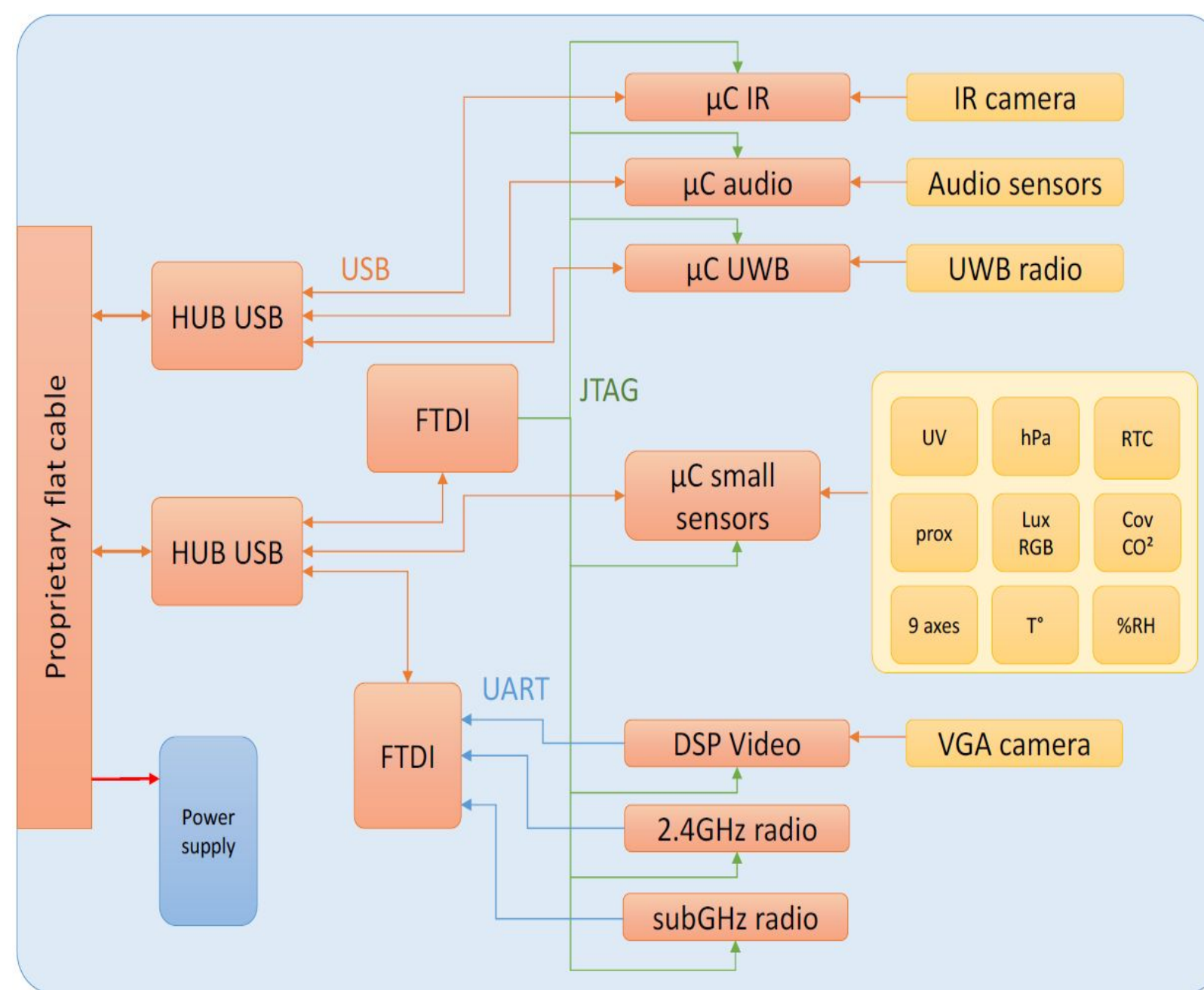
An example of NILM on the REDD public dataset House 1



Main power of a building is disaggregated to isolate single appliance power consumptions. This ensures a better understanding of the energy consumption in a building. Most of the current NILM methods have an *a priori* knowledge of the individual signatures or are trained on single appliances.

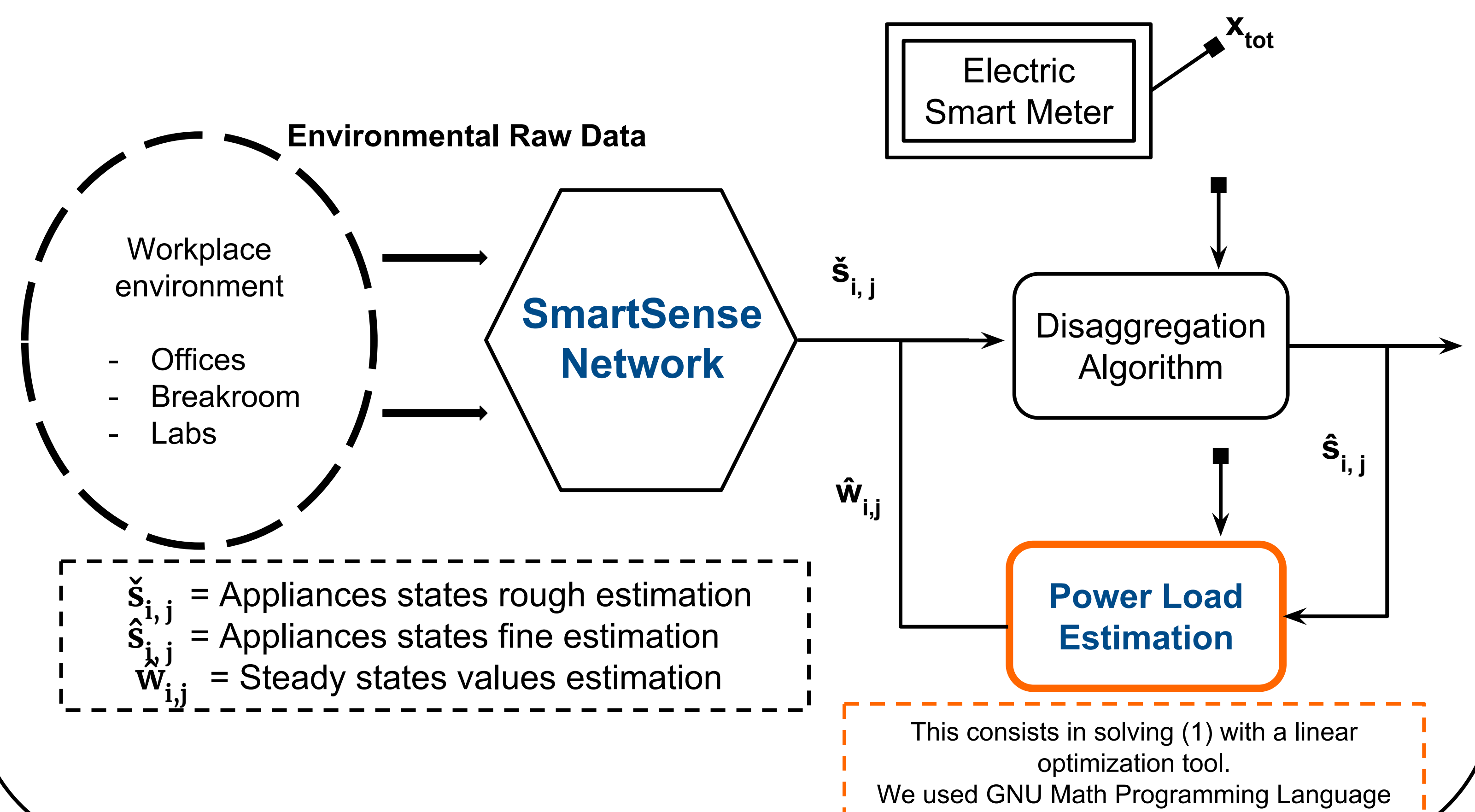
## SmartSense

- We believe that additional info can help in improving disaggregation algorithms
- Basic computations made directly on sensor node
- Ensures low network usage and user privacy
- Environment is an electronic lab
- 156 nodes are deployed
- More info and data download at [smartsense.inria.fr](http://smartsense.inria.fr)



Block-diagram of a SmartSense Node

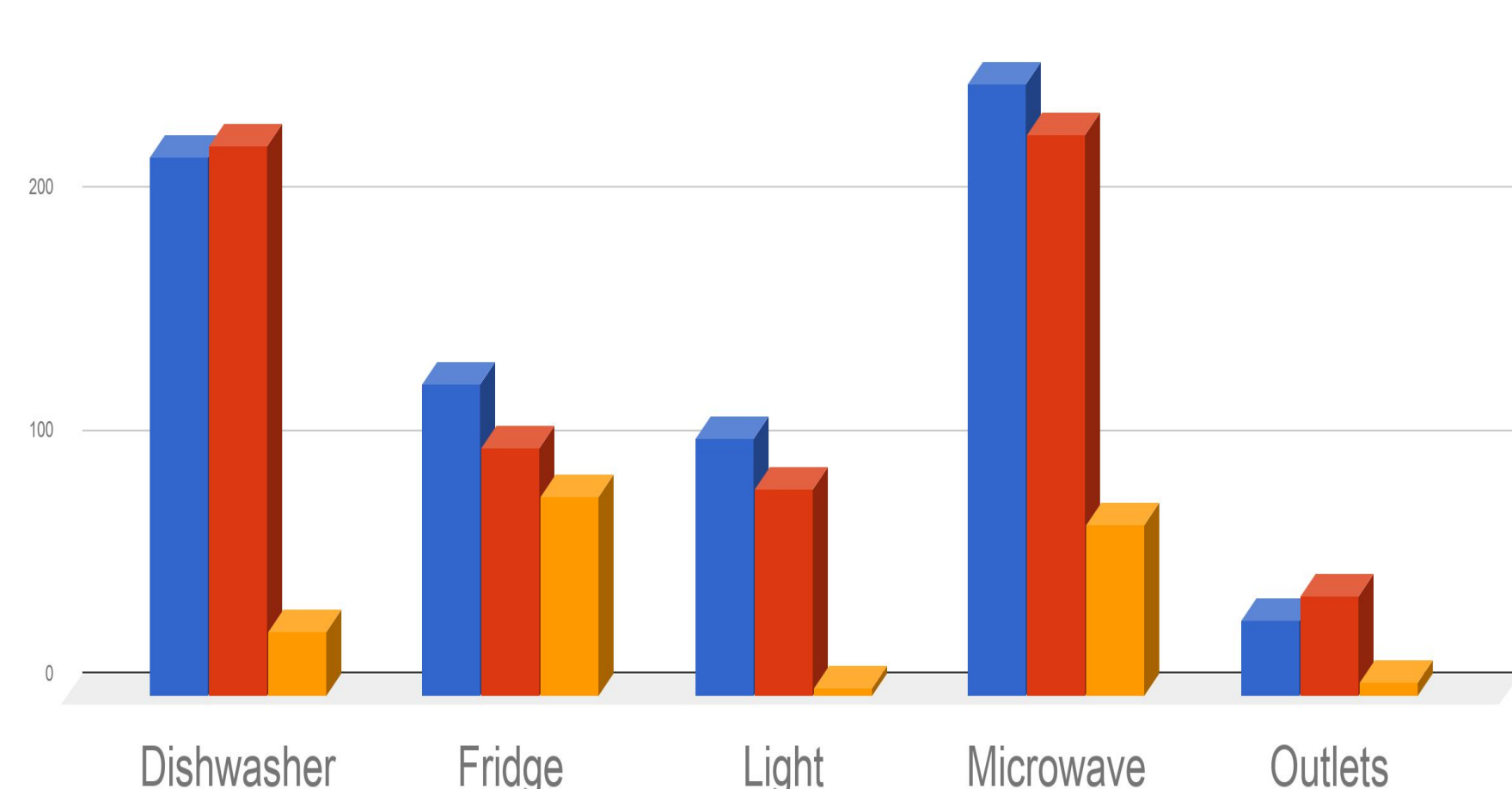
## Dataflow



## Comparison with "blind" algorithms

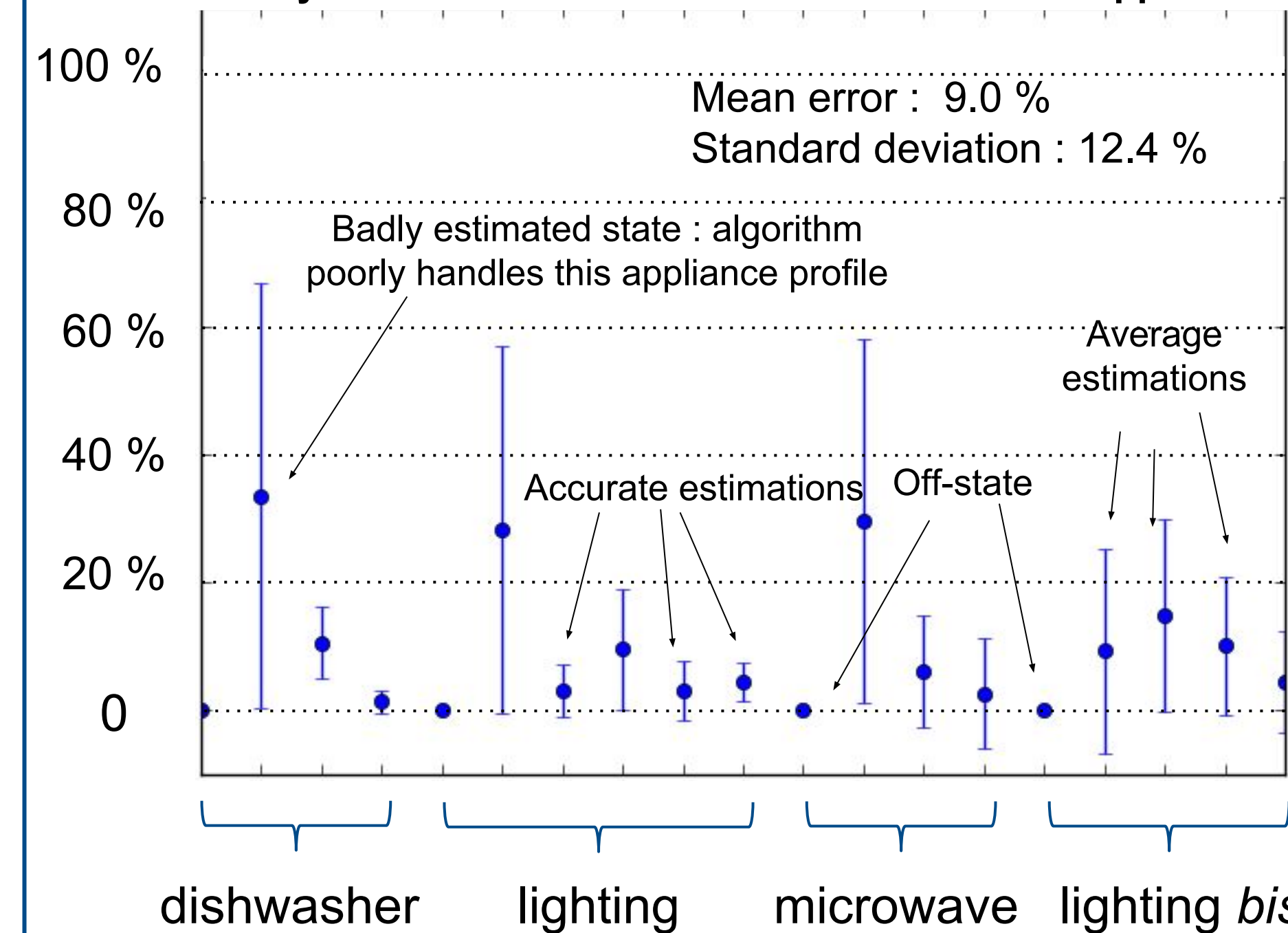
RMS error between predicted and true power for REDD 1 appliances

CO FHM Our algorithm (with appliances states knowledge)

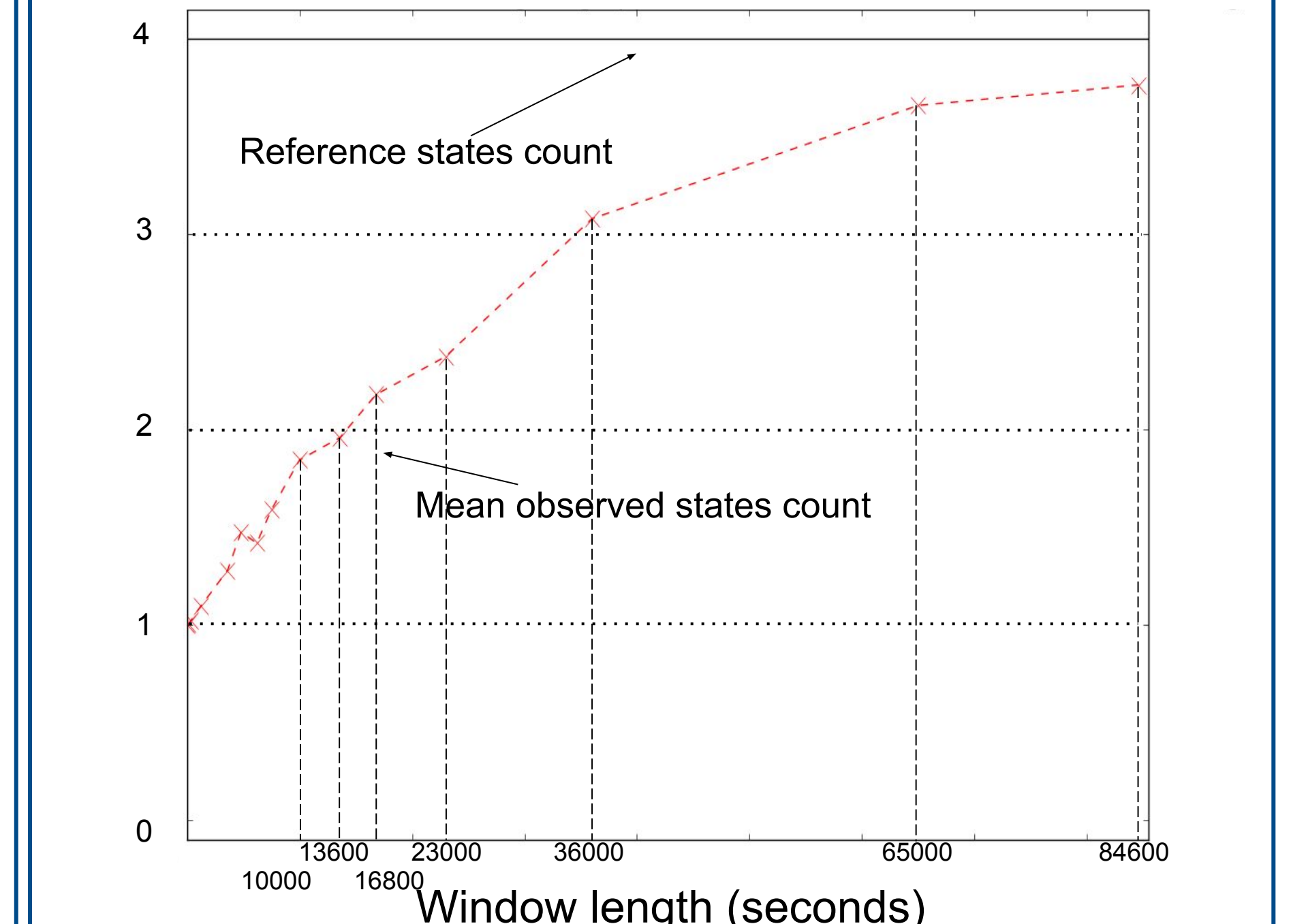


## States detection and estimation accuracy

Steady states values errorbars for various REDD appliances



Lighting circuit appliance states count



## Conclusion

- An estimation algorithm based on environmental sensing has been proposed.
- SmartSense, a sensor network with a wide range of sensors is introduced.
- Promising results are displayed in terms of complexity and prediction error, but the algorithm showed significant variations according to the nature of the appliance power time series.

## Future work

- Smartsense deployment and data collection are imminent.
- Smartsense is expected to yield accurate environmental data but inaccurate appliance states matrix.
- Next challenges to address are the algorithm robustness to this kind of errors, and association between NILM algorithms and environmental data instead of electrical data.

