HOMEpulse
SMART ENERGY SERVICES

Disaggregation of space and water heating from real life 10-minute load curves

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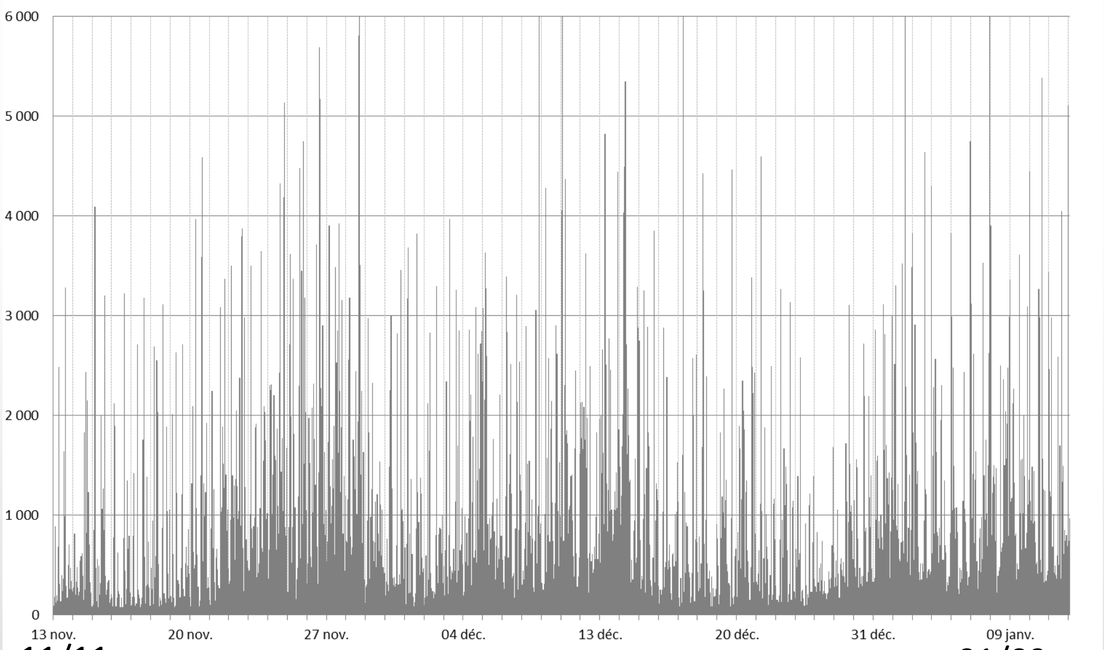
- **Ph.D. since 2013**
  - Optimization
  - Bayesian statistics
  - Signal processing

- **Researcher at Homepulse in Paris since 2013**
  - Load curve disaggregation research
  - Statistical analyses of residential electricity consumption

Smart metering in France

By 2021, “Linky” smart meters should be installed in almost every home.
They are foreseen, so far, to deliver 10-minutes consumption averages.



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- ★ What kind of **information** can 10-minute data deliver?
  A important issue for the next few months and years!

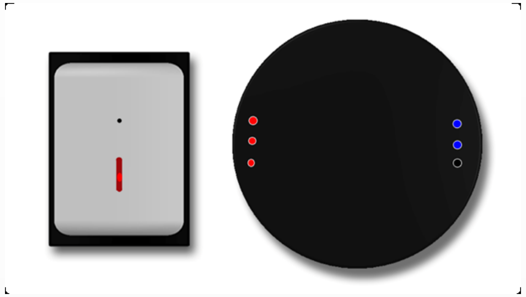
Electric space and water heating in France

- **Electric heating**
  - 31% of French homes (principal residences) use electric heating

- **Electric water heating**
  - ~45% of French homes (12 millions)
  - Most are set automatically by a load control switch
    a low frequency message send via the grid turns them on at off peak hours
  - Some water heaters are running on an “as needed” basis
    these heaters are not addressed by the scope of this presentation

Validation sample:
12 households with “ground truth” readings

- **Aggregate consumption read at the meter**
  - *Uno®* sensor reads the meter’s flashing light (1 flash *per* Wh)



- **Disaggregate Readings from some individual plug loads**
  - *Plugwise®* sensing plugs on each heater and on the water heater

a) Prises Plugwise

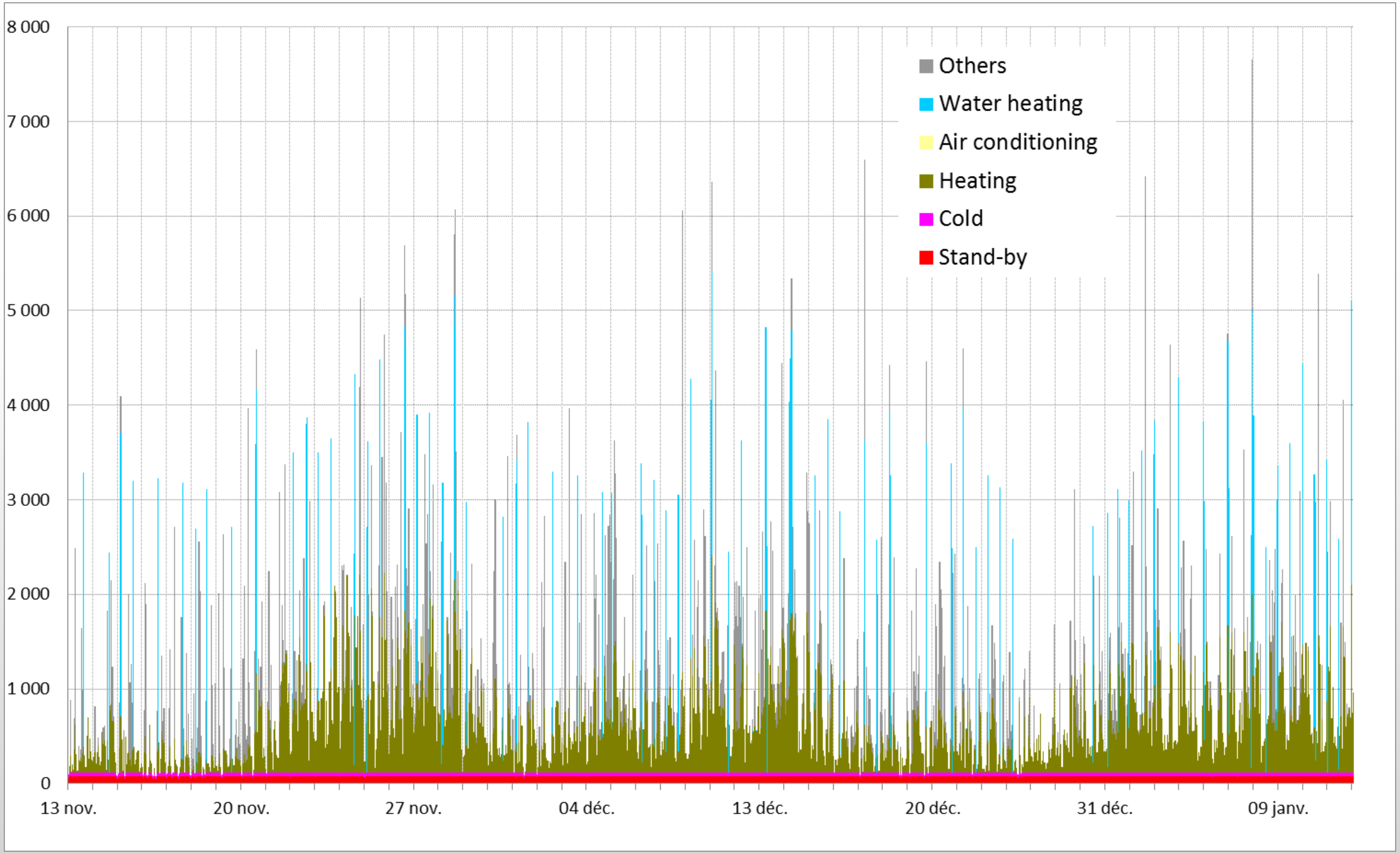
b) Passerelle Plugwise

- **We downgrade data to 10-minutes averages,** in order to simulate future Linky data

Disaggregation algorithm

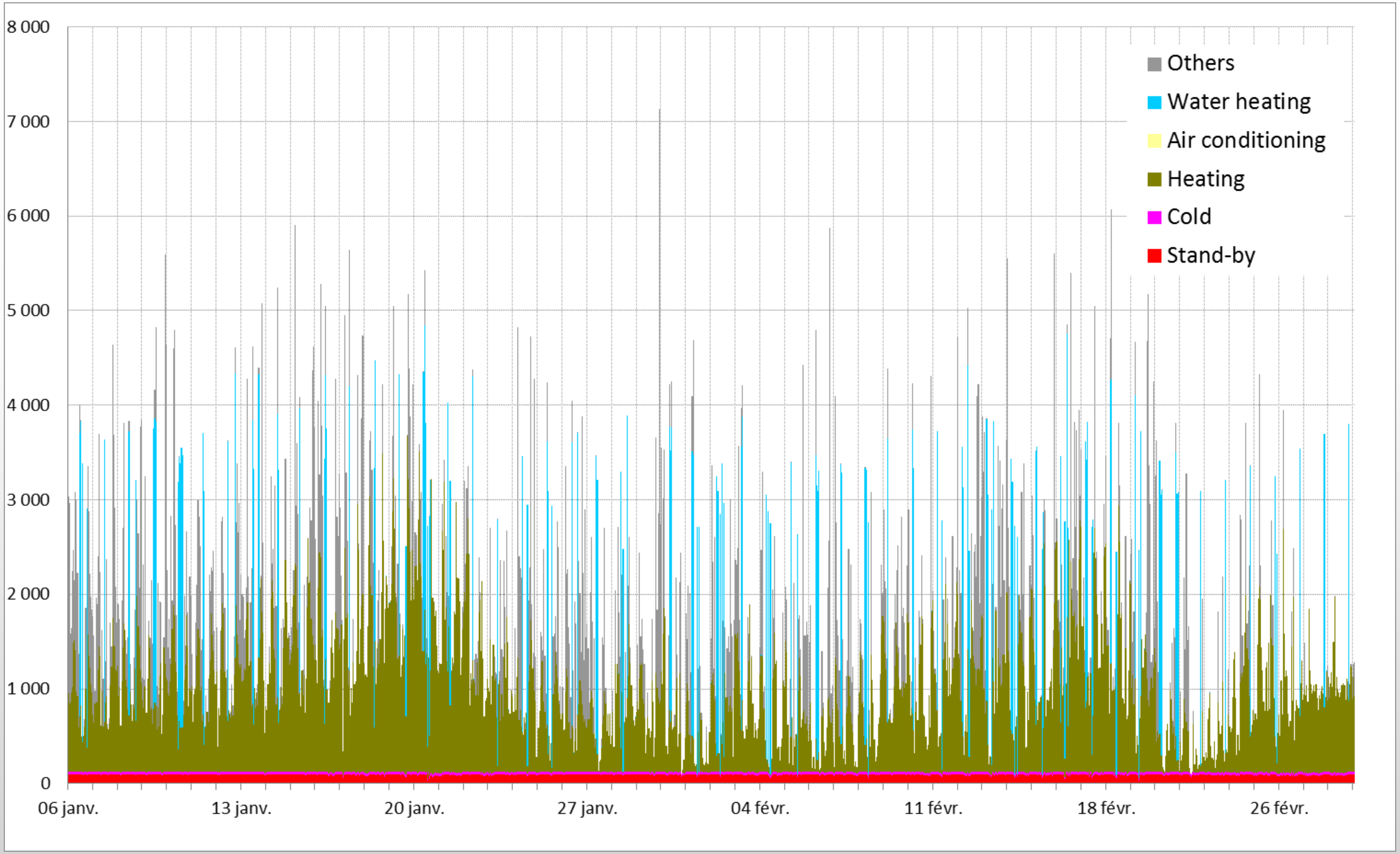
Disaggregation algorithm

Illustration 1: Household #12



Disaggregation algorithm

Illustration 2: Household #2



Disaggregation algorithm

Description

- **At each 10 minute-data value (t_k, P_k), we try to find the disaggregated consumption values X_i which optimize a cost function J**

$$argmin_{X_i} J(X_1, X_2, \dots, X_n) = \sum_{i=0}^{n} (E_i - X_i)^2 / Var_i$$

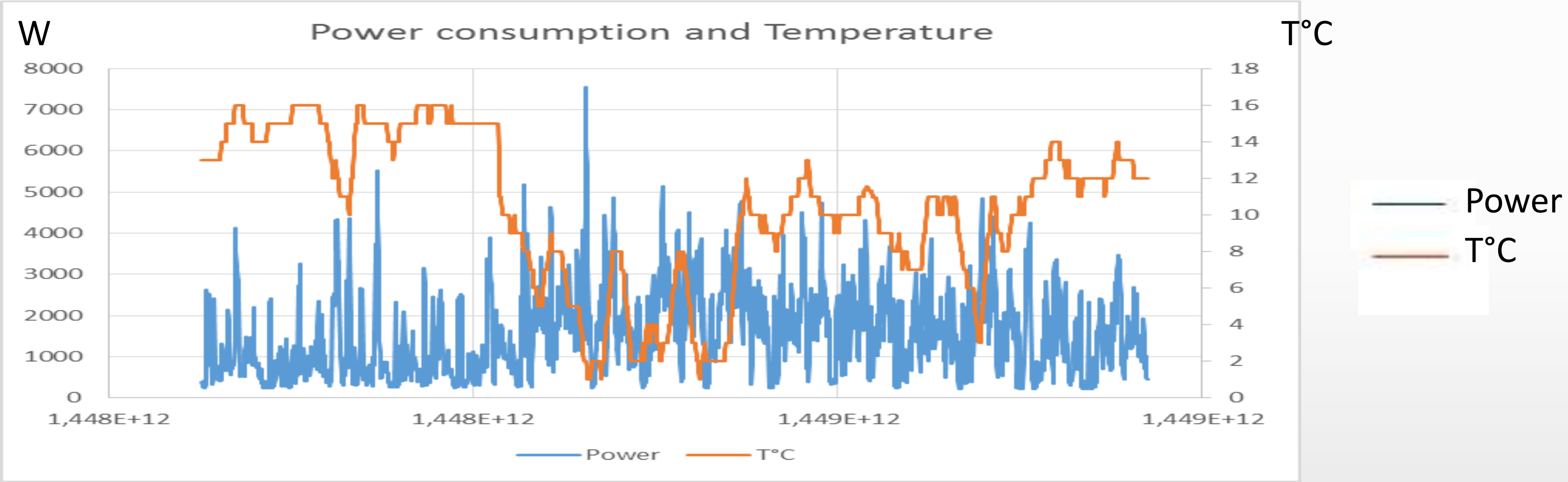
subject to $\sum_{i=0}^{n} X_i = P_k$

- **The expectations E_i and the variances Var_i are themselves estimated from specific treatments on each household 10-minute dataset**
  - Regarding heating, a "thermal gradients model" relating consumption to external temperatures, delivers heating expectations; we use the spread of residuals on cold days as a basis to estimate variance.
  - Regarding water heating, we use the time-profile of the non-thermal estimated consumption (i.e. the "intercept" of the thermal gradients model) as a basis to estimate water heating expectations; we use the spread of residuals at the same time of days with neutral temperature, in order to estimate variance.

Thermal gradient

General principles

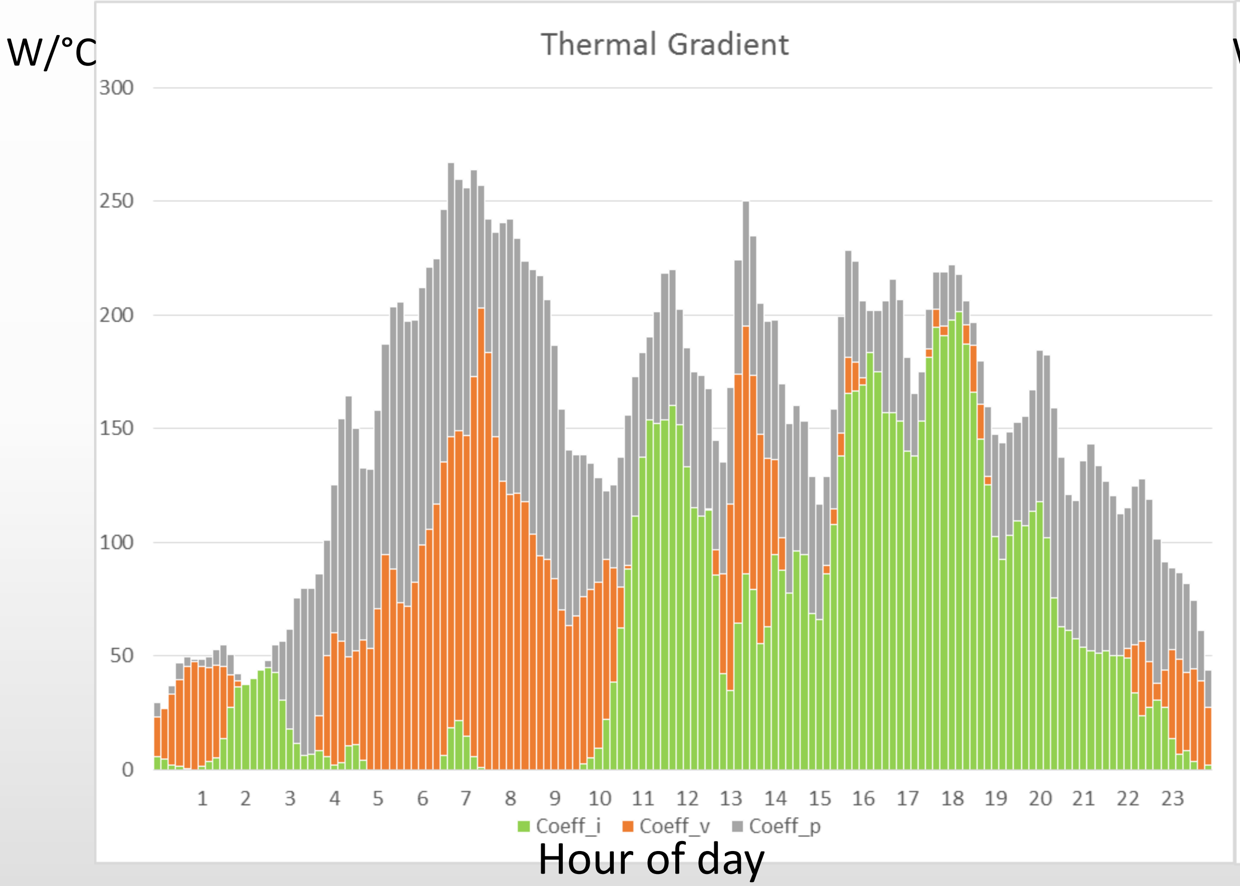
- **Looking for a linear relationship between electric consumption and outside temperatures**

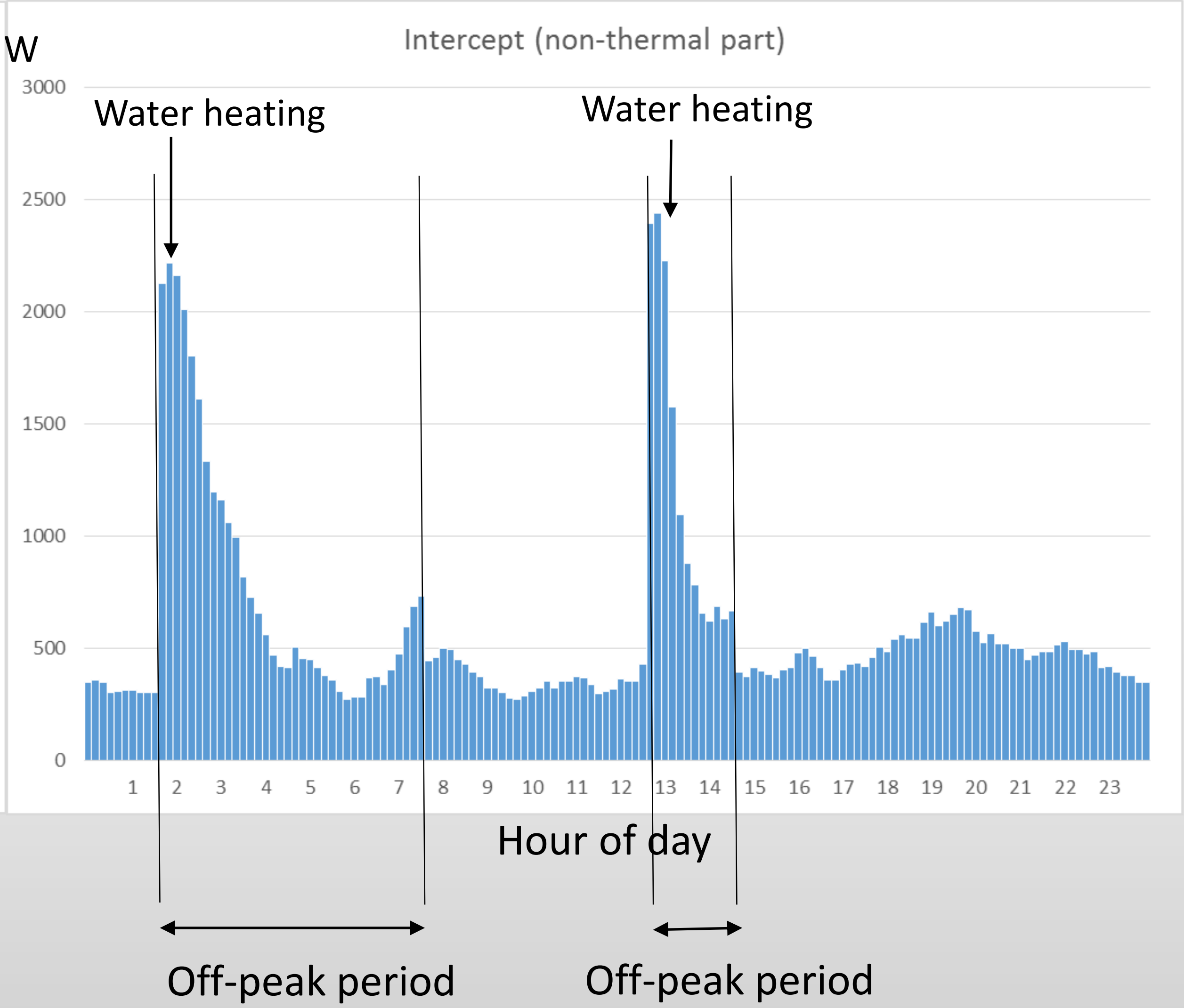


  - Lagged temperature variables catch the thermal inertia of the building
  - An additional dummy day/night variable prevents confusion of heating (thermal gradient) with lighting — the issue is esp. relevant around 19:00.
  - Heating strongly depends on the hour of the day => 144 models computed, one for each 10-minute slot. Triangular smoothing is performed on 30' slots.

Thermal gradient

Results illustration





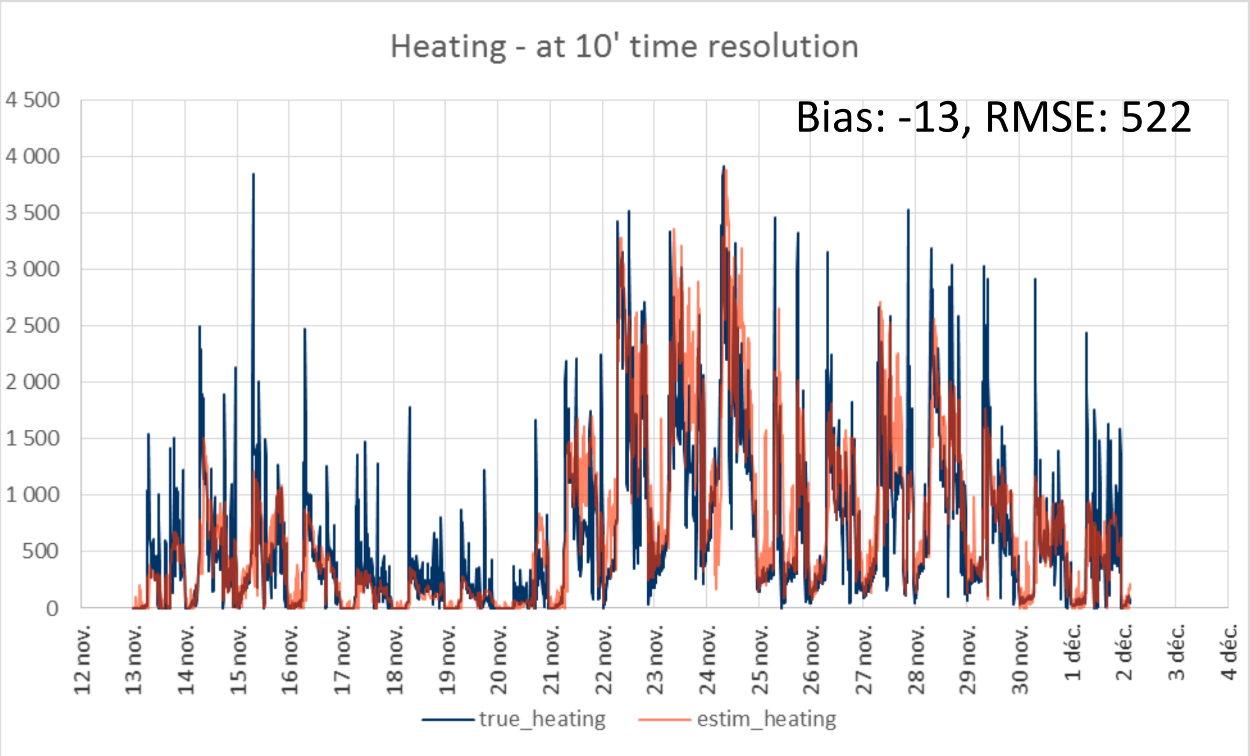
Instantaneous T°-sensitivity

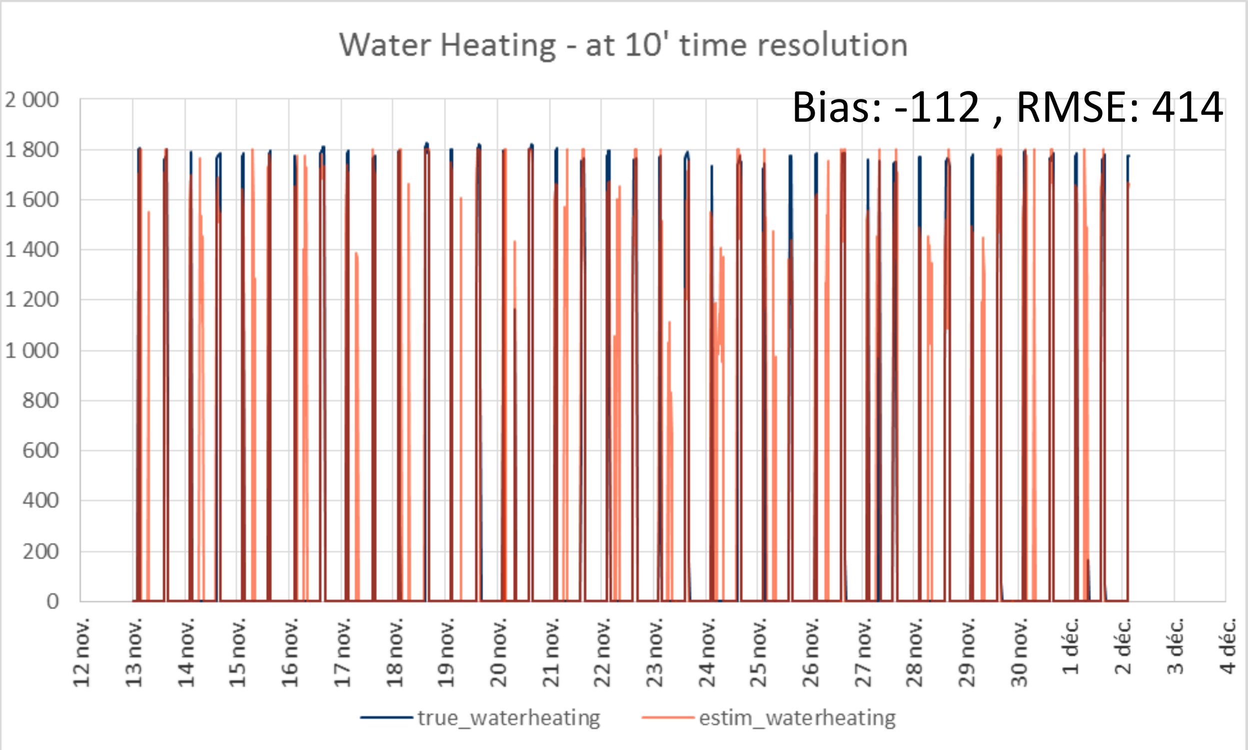
12 hour lagged T°- sensitivity

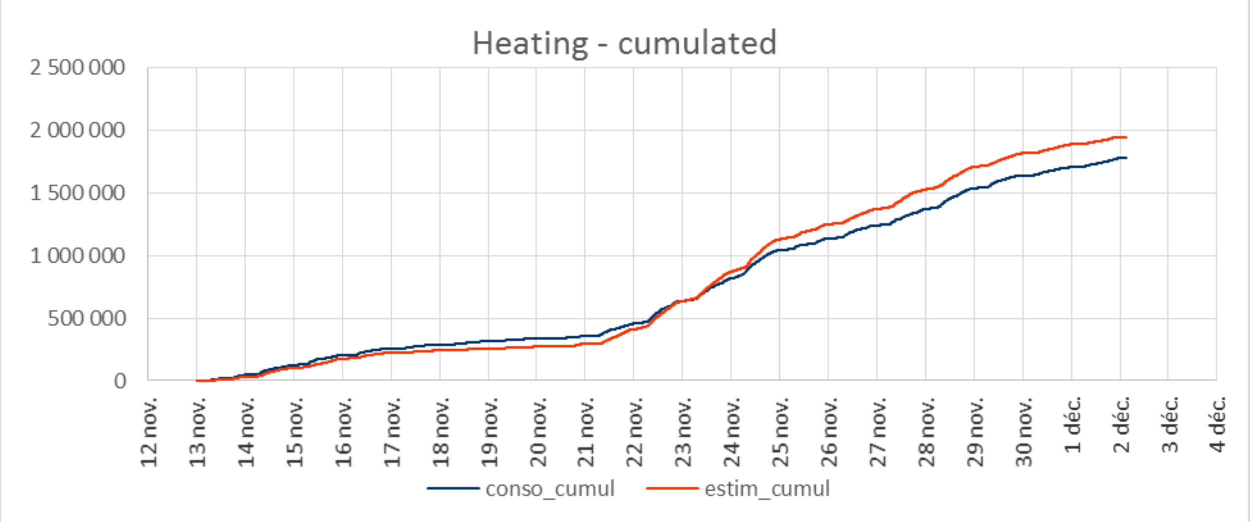
Sensitivity to previous T°, with exponential smoothing

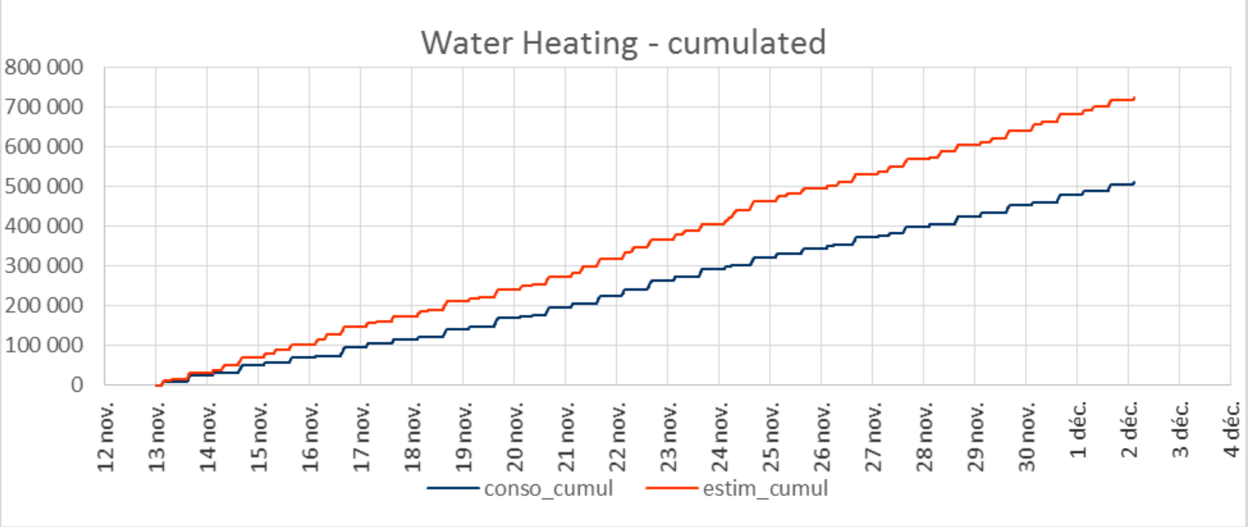
Results: Household #3

Ground truth
Estimation



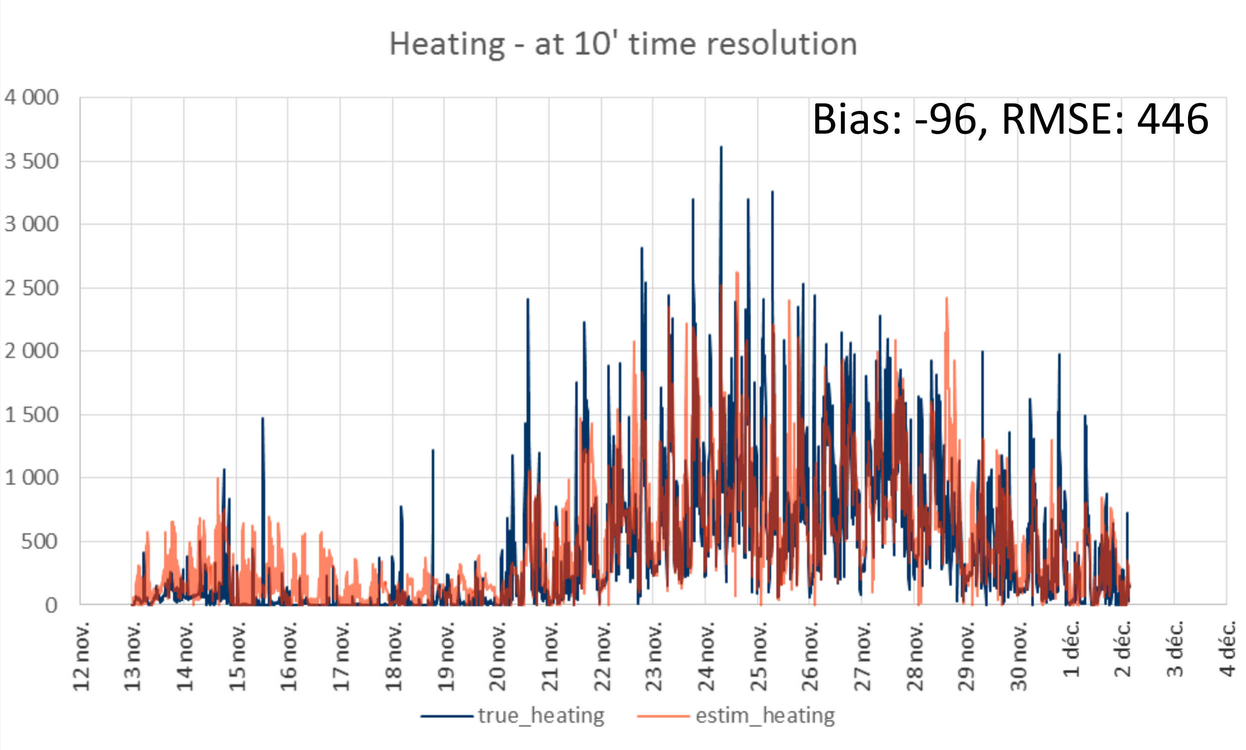


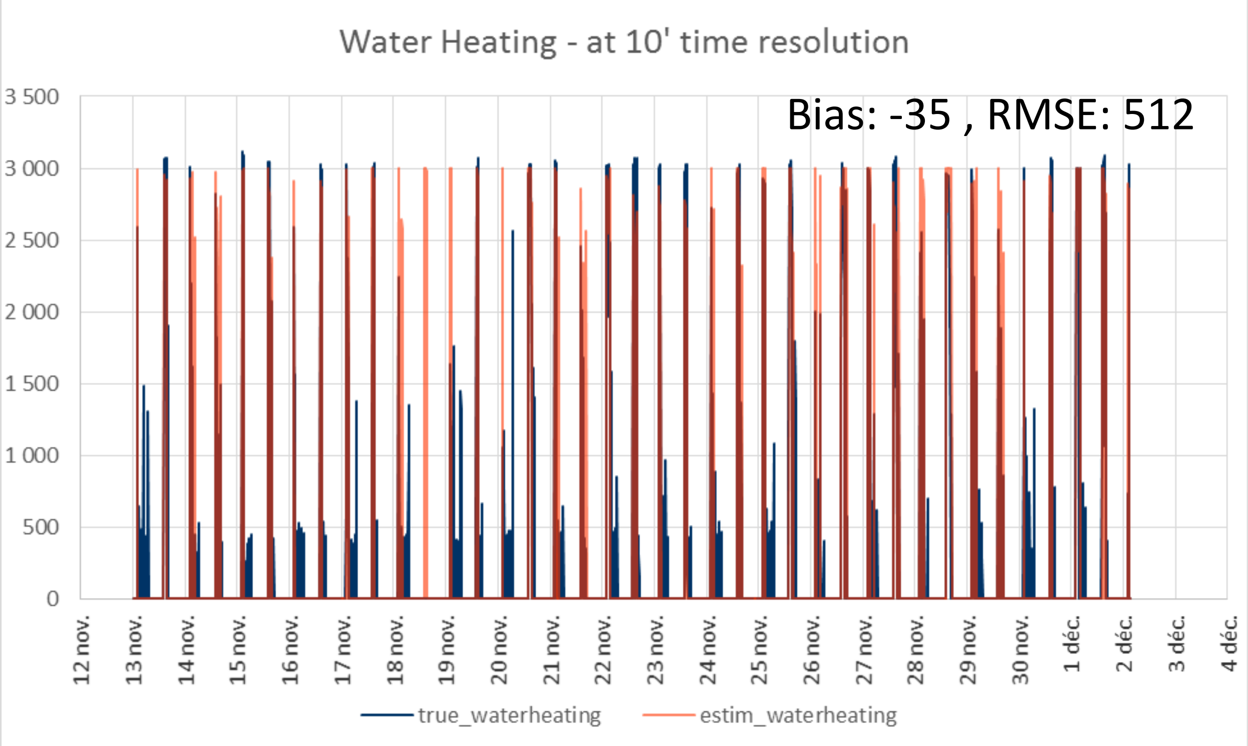


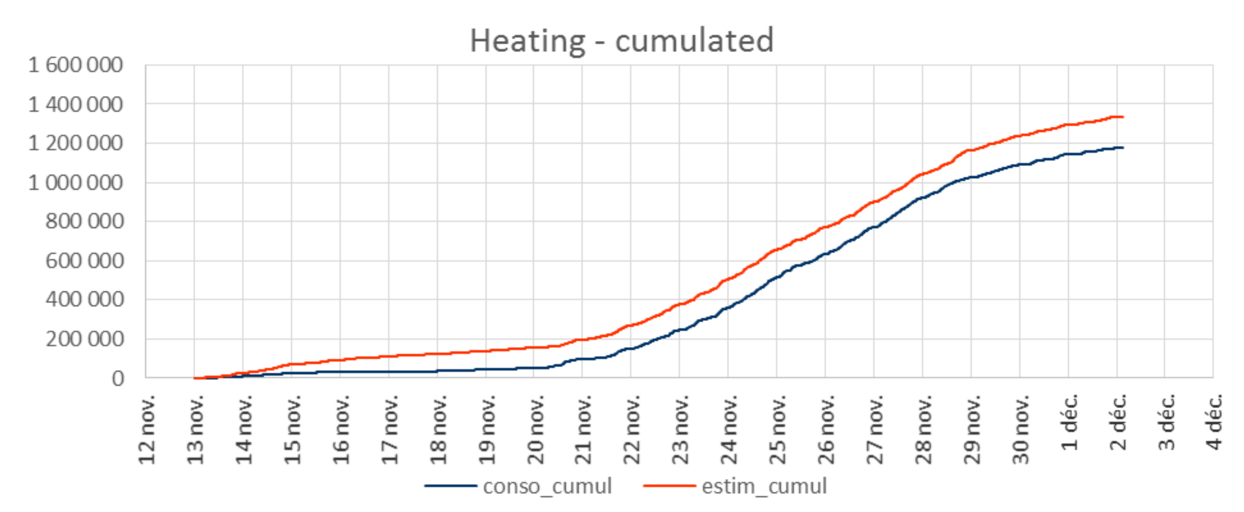


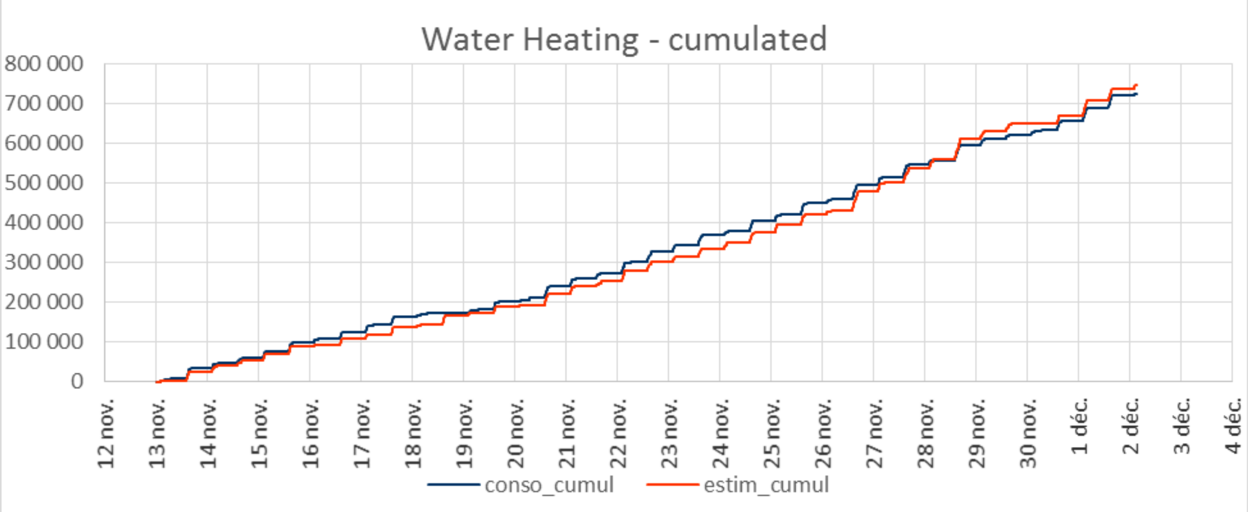
Results: Household #12

Ground truth
Estimation









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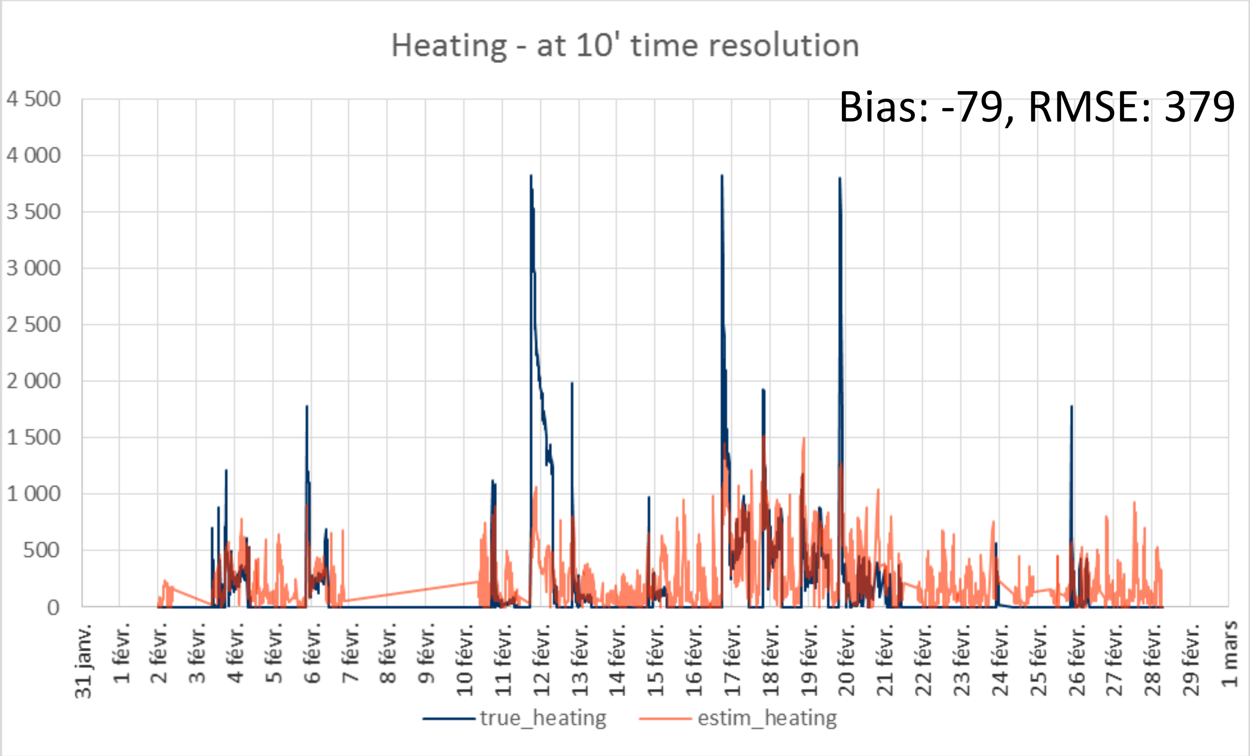
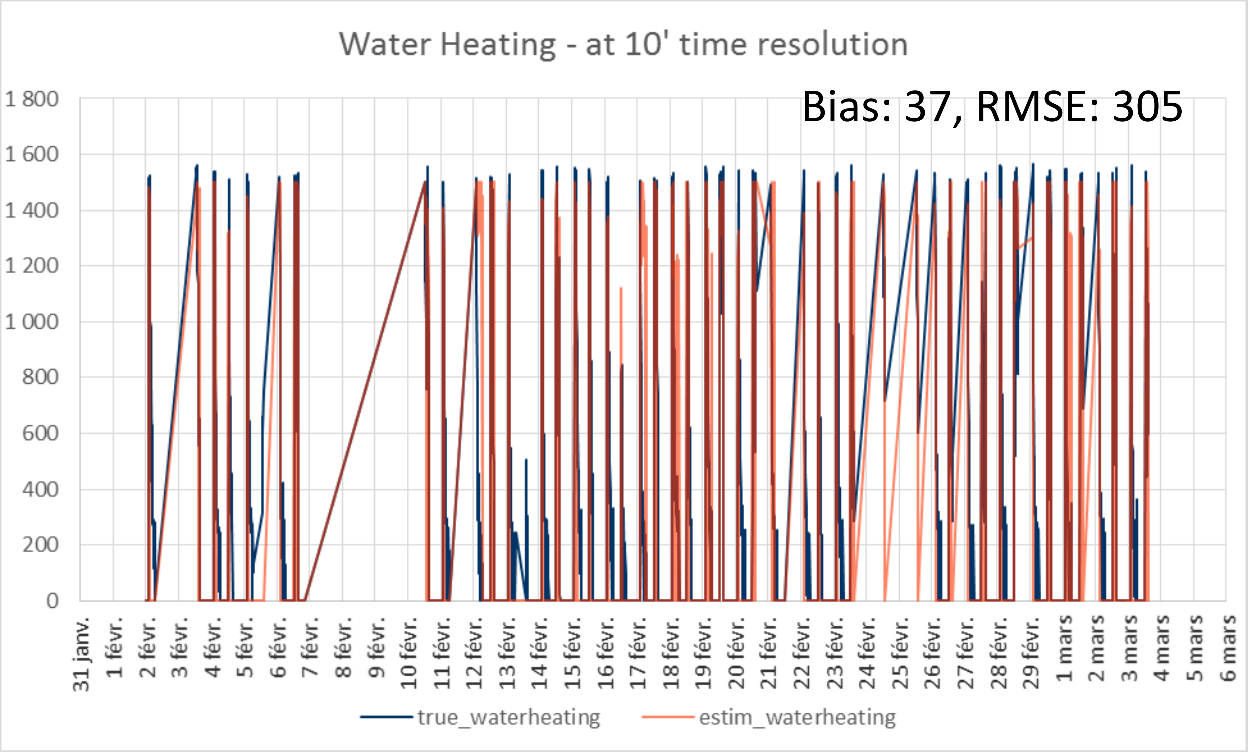
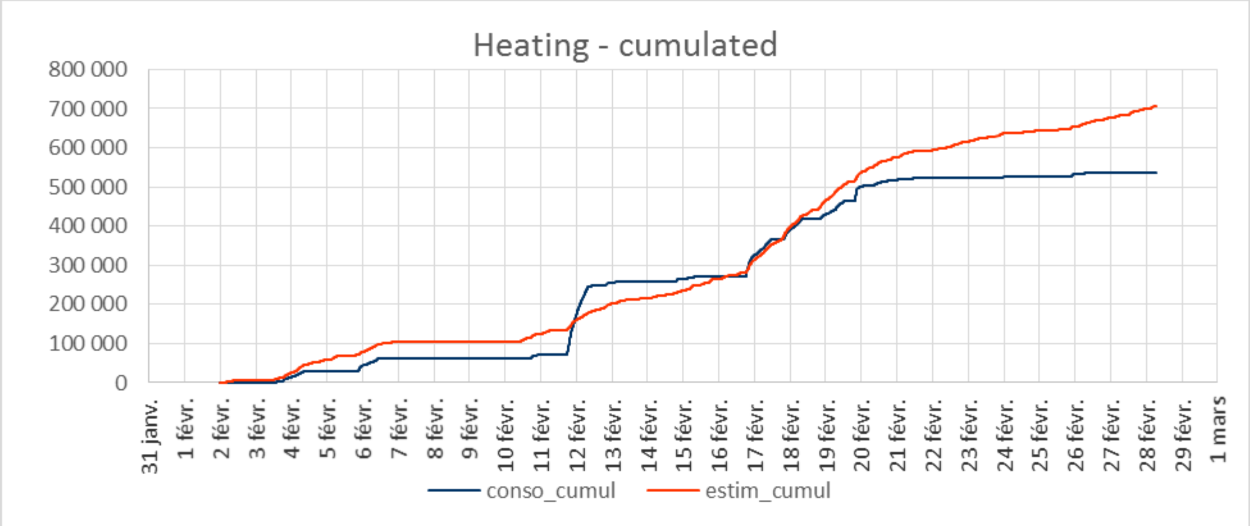
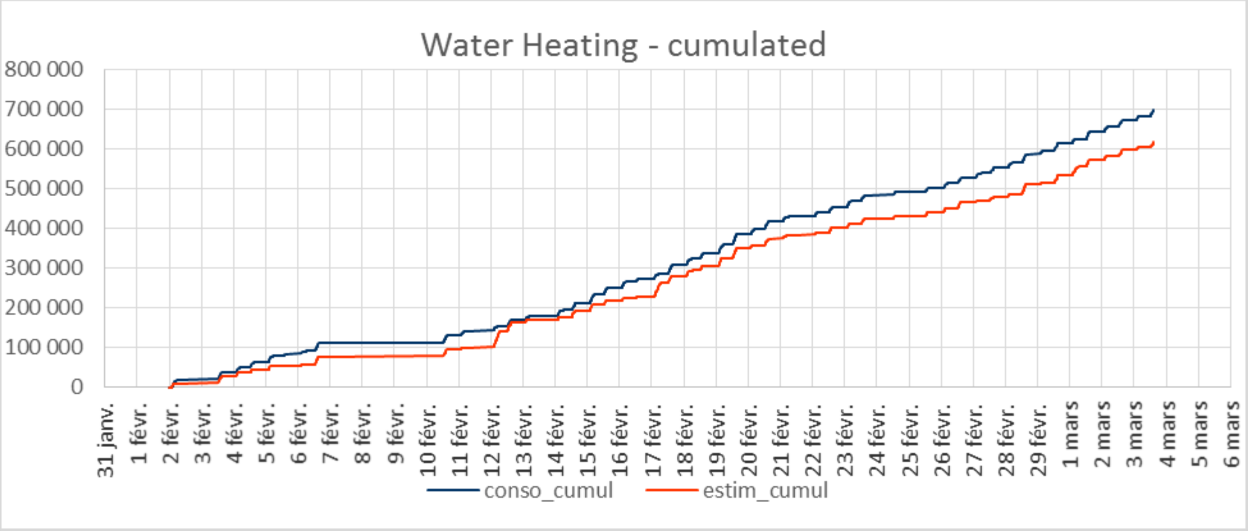
Results: Household #1

Ground truth
Estimation









Accuracy

Household n°	Heating bias W	Heating RMSE W	Water heating bias W	Water heating RMSE W
#1	**-79**	**379**	**37**	**305**
#2	16	492	-26	373
#3	**-13**	**522**	**-112**	**414**
#4	-667	1020	-225	636
#5	284	556	283	404
#6	-115	712	98	389
#7	540	957	-92	679
#8	95	405	-46	633
#9	-475	1081	55	1000
#10	467	910	-90	508
#11	39	271	51	235
#12	**-96**	**446**	**-35**	**512**

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What for

Disaggregating the 10 or 15 minute load curve as a flow

Disaggregation of costs: a strong demand from utilities

Evaluation of heating performance: implications for insulation policies/subsidizing

Smarter thermostat without additional heating consumption measurements

Anomaly detection – monitoring of homes, especially when not occupied by owners

Currently working on…

- **Other appliances:**
  - HVAC
  - Lighting
  - Off-peak-hours triggered water heaters at other times of day
  - Other kinds of water heaters
  - Pool pump
  - …
- **Dynamic consumption forecast:**
  - Withdrawing the assumption that 10’ time slots are independent from each other
  - Combining the statistical approach in the present paper, with dynamic modeling.

A Unique Positioning

From energy consumption data to meaningful technology and marketing events

STATISTICS, MATHS, MODELS

ALGORITHMS
- **5'' DATA**
- **10'+ DATA**

AD HOC ANALYSES

ENERGY MANAGEMENT SERVICES

CUSTOMER INTERFACES

MONITORING TOOLS FOR ENERGY SUPPLIERS

MEASUREMENT ON HOUSEHOLDS SAMPLES, TARGETING
- **ENERGY CONSUMPTION**
- **USAGES**
- **ELECTRICITY / GAS, 1''… 1h**

- Load curve disaggregation
- Thermal 'gradients' model
- Forecast (30', month, years)
- Anticipation of peaks
- Prediction of churn,…
- Detection of devices
- Demand response potential

- Customer engagement
- Interactive advice
- Simulation tools
- Comparison vs. references
- Consumer databases creation
- Gaming

- Permanent households panel "PowerMetrix"
- Ad hoc samples recruitment, equipment and measurement
- Demand Response Testing
- Evaluation of the savings impact of a new equipment
- Before/after & with/without

Our Assets

From energy consumption data to meaningful technology and marketing events

- ✓ **Patented disaggregation algorithms**: meter load curve / electrical appliances load curve
- ✓ **IT Big Data architecture** (Cassandra, MongoDB, Akka Streams, Google cloud,…)
- ✓ **Hardware experience** from the last 3 years' projects (meter sensors, smart plugs, electricity & gas)
- ✓ **Team** of high level data scientists, big data engineers and seasoned entrepreneurs

References