# Non-Intrusive Load Monitoring of Single and Aggregated Profiles with a Hidden Markov Model

Let's make sense of energy

Nadège Miquey
Ecole centrale de Lyon
Lyon, France
nadege.miquey@ecoco2.com

Etta Grover-Silva
Eco CO2
Nanterre, France
etta.grover-silva@ecoco2.com

## Etta Grover-Silva

**Data Scientist**
Eco CO2
Nice, France

Responsible for analysis of electric load data for residential, commercial and educational buildings. Current tasks include the exploration of data using supervised and unsupervised techniques as well as the development of disaggregation algorithms and predictive models for load profiles.

## Education

**PhD MINES ParisTech**
Thesis topic: The optimization of planning and operations of the distribution grid in the context of high renewable energy penetration.

**M.S. Loughborough University**
Specialization: Hybrid systems (Kassel, Germany)

**B.S. Engineering Smith College, MA, USA**
Specialization: Alternative energy systems

# Key facts

Eco CO2 is an environmentally oriented company contributing to innovative projects as well as social and solidary programs

AGRÉMENT
ENTREPRISE SOLIDAIRE D'UTILITÉ SOCIALE

**2009**
Founded

**82**
Employees

**7**
National awareness raising programmes (financed through French energy saving certificates)

**2**
IT projects funded through the Investments for the Future programme (ADEME)

**2**
R&D projects developed with equity capital

**€ 5.7M**
2019 turnover figures

# Our main activities

## Awareness raising programs

- **Assist** individuals and organisations better understand the impact of their actions on the environment
- **Accompany** behavioural changes
- **Implement** programmes with local partners

## Technological developments

- **Develop** multi-service platforms for environmental data (energy, mobility)
- **Create** connected objects to help control energy consumption and improve the comfort of buildings

## Data driven studies

- **Offer** studies and advice on energy management
- **Carry out** behavioural studies to better support change
- **Design** algorithms to model energy predictions or energy optimisation

# Context

## Energy transition

### Future electric grid

- Decentralized generators increasing in market shares that have a high variability and low predictability
- Electric load is growing
- Europe has ambitious goals to reduce electric consumption of the building sector
- Building energy use is highly variable based on end user habits

### Awareness raising programmes

- Eco CO2 has developed tools to collect data and accompany end-users to reduce their energy use and optimize their consumption
- Most effective advice to change end-user behaviour is time and appliance specific
- Each household has a different capacity to reduce their enegry use

# Methodology

- Explore algorithms that are capable of automated detection of a single appliance profile
- Test algorithm on single and aggregated appliance data
- Study the performance of the algorithm on degraded resolution

## Pre-processing

- KMeans clustering and data feature extraction
- Interpolation and bucketing of aggregated profile
- Test and training on data set

## Construct Hidden Markov Model

- Single appliance model
- Multi-apppliance model

## Evaluation metrics

- Single and multi-appliance model evaluation

# Case study

## 64 smart plugs data

Internal experimental study with Eco CO2 employees to monitor household appliances during a 6 month period

## 3800 days of data

Historical data used for training models

**Kitchen appliances**

- Hot water boiler
- Refrigerator
- Coffee machine
- Washing machine

**Multimedia appliances**

- External screen
- Internet router
- Laptop charger
- Television

TABLE I
KMEANS CLUSTERING, SAMPLING RATE = 5 SECONDS

| Appliance type | Duration of training timeseries (days) | Number of active periods |
|---|---|---|
| Hot-water boiler | 10 | 21 |
| Refrigerator | 3 | 94 |
| Coffee-machine | 10 | 29 |
| Washing-machine | 10 | 10 |
| Screen | 3 | 8 |
| Internet router | 3 | NA[a] |
| Laptop charger | 6 | 8 |
| Television | 5 | 12 |

[a]Not Applicable, internet router is an always on appliance.

TABLE II
KMEANS RESULTS, SAMPLING RATE = 1 SECONDS

| Appliance category | Appliance type | Number of clusters | Clusters centroids (W) |
|---|---|---|---|
| Kitchen appliances | Hot-water boiler | 2 | [0.3839, 2468] |
| | Refrigerator | 3 | [0.1490, 117.7, 1269] |
| | Coffee-machine | 2 | [1.417, 1576] |
| | Washing-machine | 2 | [2.813, 2438] |
| Multimedia appliances | Screen | 2 | [1.0, 29.06] |
| | Internet router | 2 | [0.0, 8.122] |
| | Laptop charger | 2 | [13.04, 0.015] |
| | Television | 2 | [0.0, 129.4] |

# Results

## Kitchen appliances

TABLE V
SINGLE APPLIANCE HMM RESULTS ON PRE-PROCESSED LOAD PROFILES FOR KITCHEN APPLIANCES, SAMPLING RATE = 1 SECOND

| Appliance category | Appliance type | Accuracy (%) | Precision | f1-score |
|---|---|---|---|---|
| Kitchen appliances | Hot-water boiler | 99.9 | 0.97 | 0.98 |
| | Refrigerator | 99.9 | NA[a] | NA[a] |
| | Coffee-machine | 99.2 | 0.72 | 0.72 |
| | Washing-machine | 99.3 | 0.99 | 0.98 |

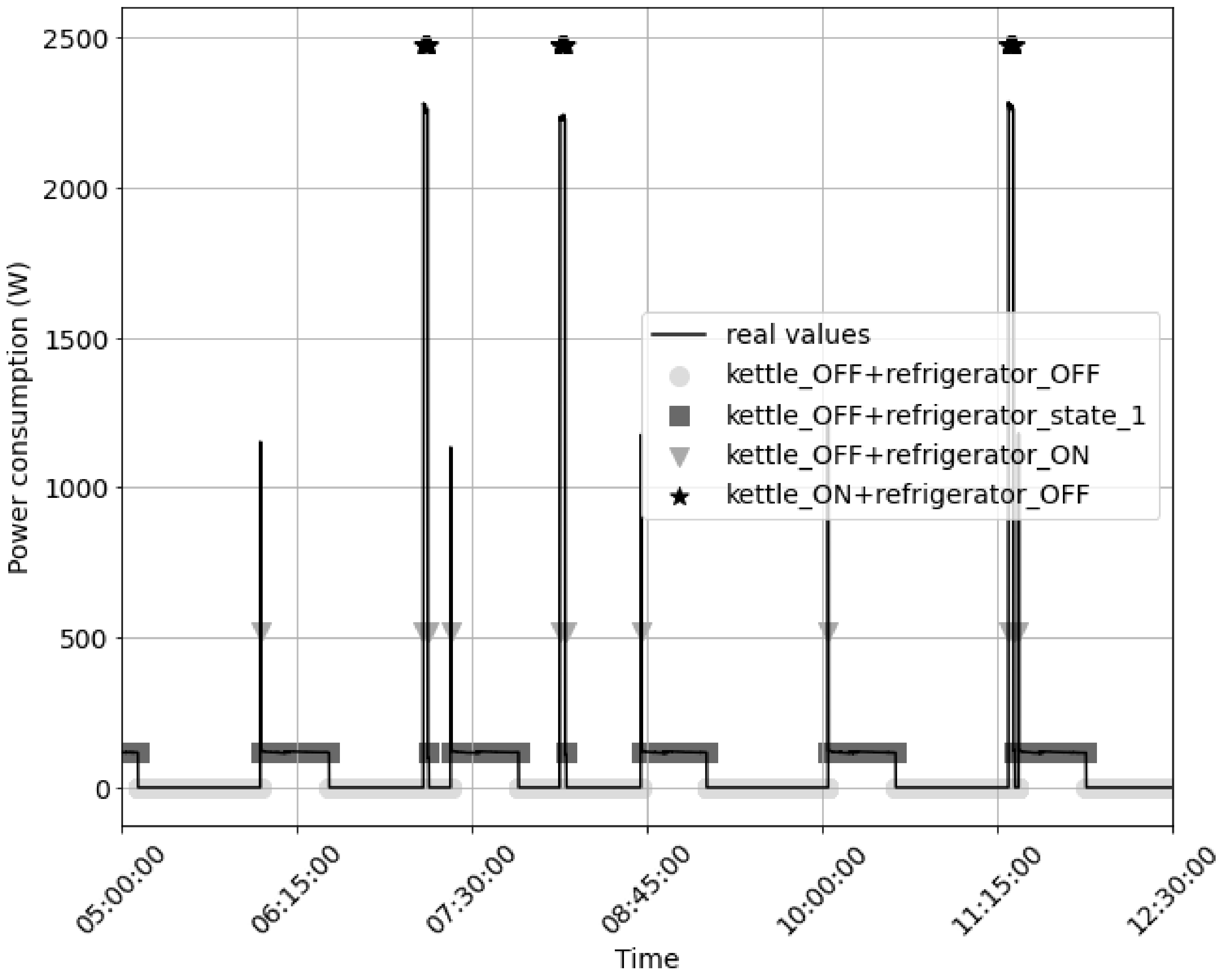
[a]Not Applicable, refrigerators are 3-states appliances

## Multimedia appliances

TABLE VI
SINGLE APPLIANCE HMM RESULTS ON PRE-PROCESSED LOAD PROFILES FOR MULTI-MEDIA APPLIANCES, SAMPLING RATE = 1 SECOND

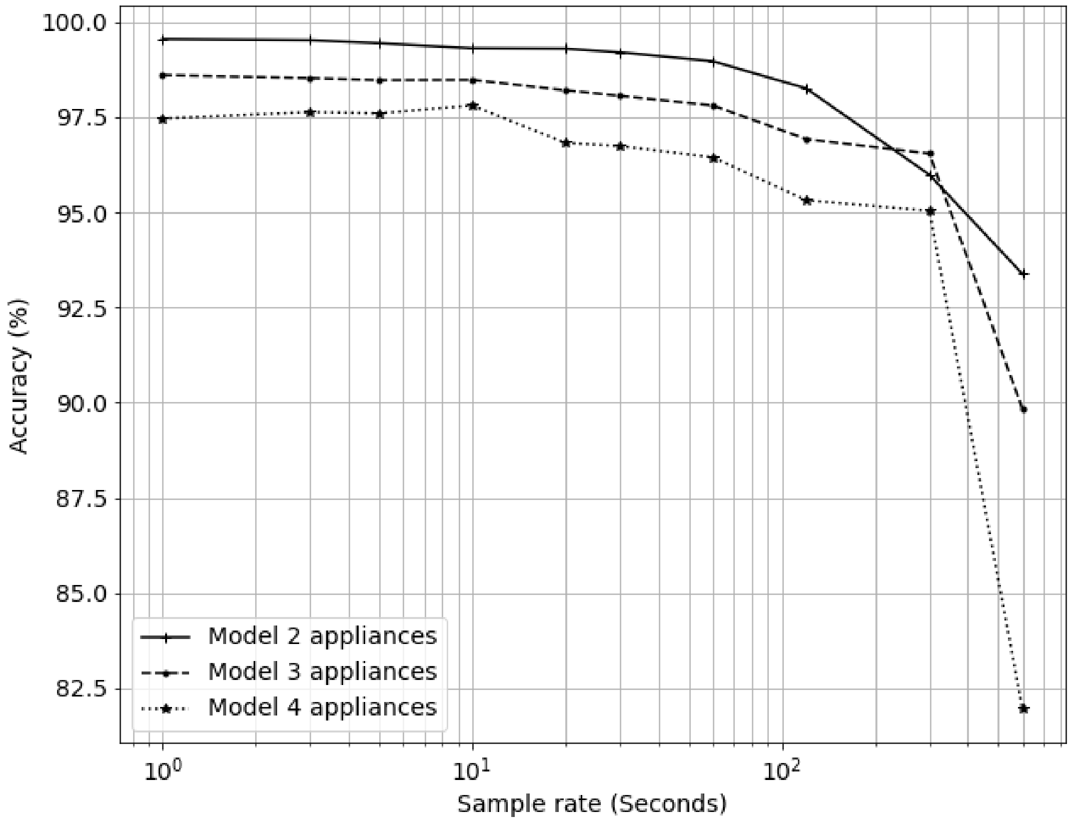
| Appliance category | Appliance type | Accuracy (%) | Precision | f1-score |
|---|---|---|---|---|
| Multimedia appliances | Screens | 99.9 | 0.99 | 0.99 |
| | Internet router | 100 | NA[a] | NA[a] |
| | Laptop charger | 94.2 | 0.99 | 0.91 |
| | Television | 99.9 | 0.99 | 0.99 |

[a]Not Applicable, internet router is an always on appliance.



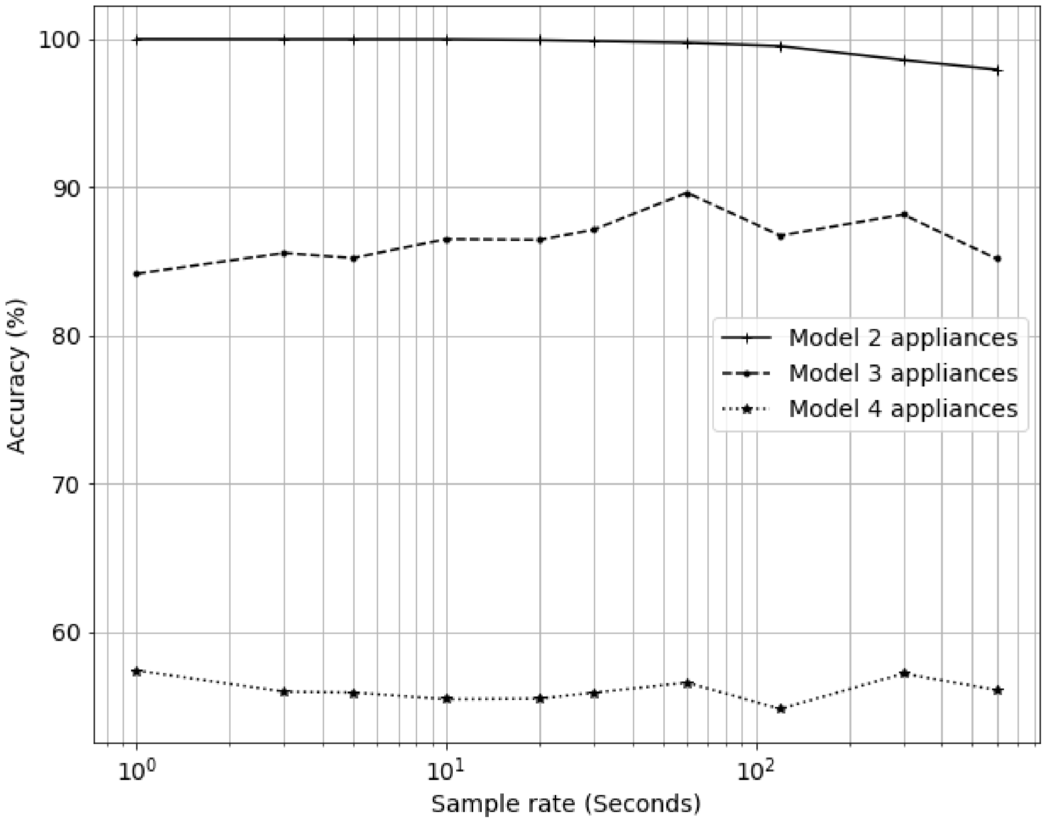
# Results

## Kitchen appliances




On and Off state prediction accuracy results (%) versus sample rate (Seconds) for combined kitchen appliances models

## Multimedia appliances




On and Off state prediction accuracy results (%) versus sample rate (Seconds) for combined multi-media device models

# Conclusions

HMM applicable to single and aggregated appliance profiles

High performance for individual models and combined kitchen appliance models

Low performance for combined multi-media appliance models

Future work :

- Develop hybrid method to overcome difficulties of similar multi-media profile shapes and magnitudes
- Compare developed models with existing non-intrusive load monitoring algorithms such as the NILMTK python package
- Apply model to other open data sources for comparison

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Donnons du sens à l’énergie


Etta Grover-Silva

etta.grover-silva@ecoco2.com


www.ecoco2.com