DEVICE USAGE ESTIMATION ALGORITHM

Residential NILM in unsupervised manner

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INTRODUCTION:

Non Intrusive Load Monitoring (NILM) is a powerful technique to provide insight to residential customer and achieve energy savings and demand side management[1]. Most NILM algorithm are based on supervised machine learning method and require higher sensing capabilities than what most common smart meters can offer. Additionally, labelled data are expensive to acquire and supervised method are hard to apply on a generic scope. Hence, we propose fully unsupervised method that require only active power measurement sampled at 15min time period.

CATEGORICAL DISAGGREGATION

Category	Appliances	Related activities
Cooking	Coffee maker, stove, oven, microwave, kettle	Cook, eat
ICT	Printer	Use computer, work, homework
Housekeeping	Washing machine, dishwasher, tumble dryer, vacuum cleaner	Clean, wash dishes, laundry
Entertainment	TV, stereo, PC, TV box, laptop, DVD, gaming console	All
Light	Lights	All
Fridge	Fridge, freezer	
Heating	Hairdryer, HP, boiler	Shower
Standby	Modem	

INPUT

Household characteristics:

- Age (G)
- Employment state (E)

Day type (D), Weekday, weekend

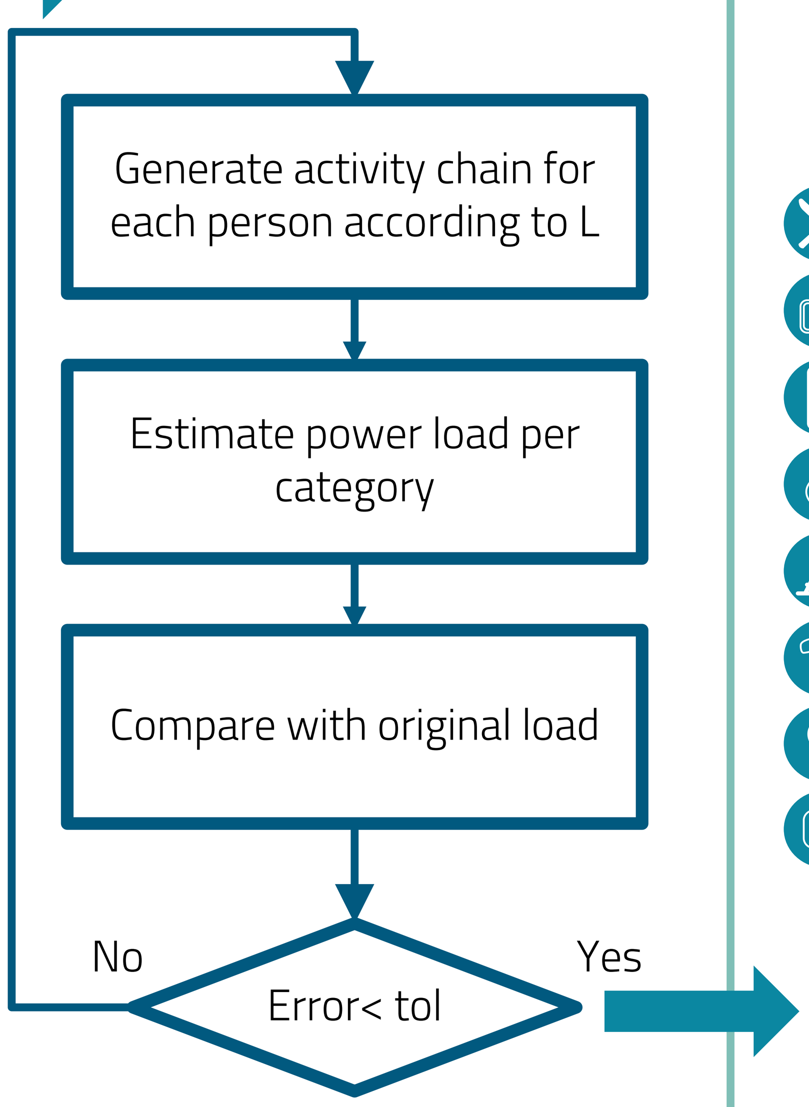
Active power load curve (L)

PARAMETER

Activity probability per:

- Time of the day
- day type
- Population group

ALGORITHM

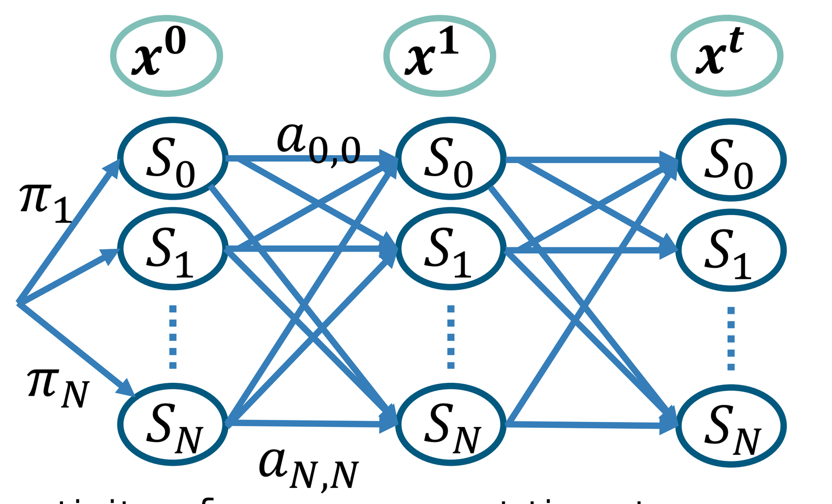


OUTPUT

Load per category:

- Cooking
- Entertainment
- Fridge
- Heating
- Housekeeping
- ICT
- Light
- Standby

ACTIVITY CHAIN GENERATION: MARKOV PROCESS



x^t: activity of one person at time t

S_i: set of possible activities according to power budget L

π_i: Initial activity probability, $P(x^0 = S_i)$

$a_{i,j}$: transition matrix, $P\left(x^t = S_i \middle| x^{t-1} = S_j\right)$

$\pi_i, a_{i,j}$ are function of G,E,D

$a_{i,j}$ is also a function of the hour of the day and adjusted according to power budget

BENCHMARKING

Supervised Algorithms

- Combinatorial Optimization[3] (CO)
- Factorial Hidden Markov Model[3] (FHMM)
- Graph Signal Processing[4] (GSP)
- Discriminative disaggregation via sparse coding[5] (DDSC)

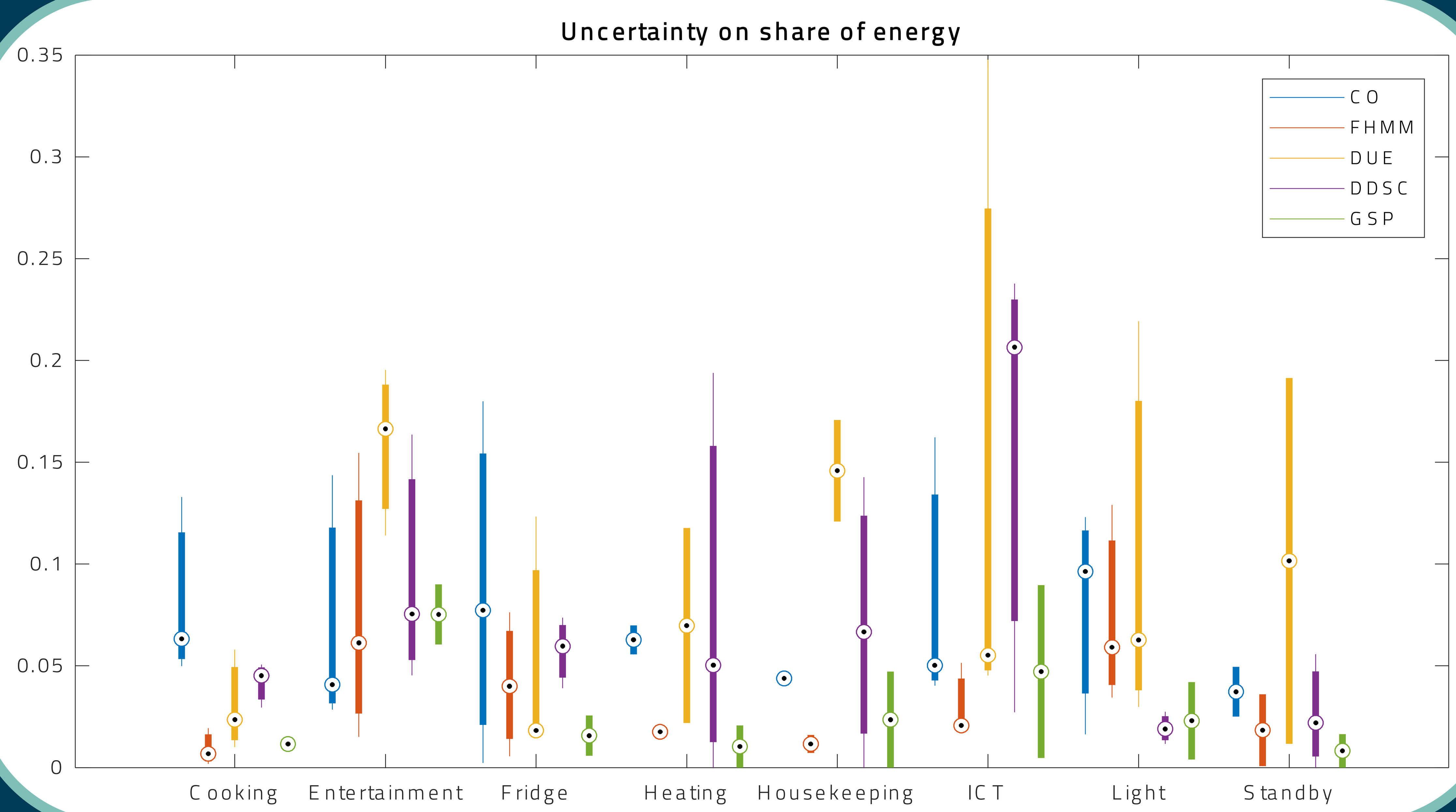
DATASETS		
	Training days	Testing days
ECO[6]	121	29
SMARTENERGY.KOM[7]	75	37
UK-DALE[8]	365	91

METRIC:

Error on category share: $E_m = \frac{\sum_t \hat{P}_m^t}{\sum_m \sum_t \hat{P}_m^t} - \frac{\sum_t P_m^t}{\sum_m \sum_t P_m^t}$

Normalized mean square error: $NMSE_{\ m} = \frac{\sum_t \left(\hat{P}_m^t - P_m^t\right)^2}{\sum_t \left(P_m^t\right)^2}$

Where $\hat{P}_m^t$ and P_m^t are respectively the estimated and reference (ground truth) power profile for category m.



CONCLUSION:

We presented an unsupervised NILM algorithm that requires low sampling frequencies. The results shows it performs in the same range as standard supervised algorithm of the field, while it's computational cost scale linearly with the test period length. As the algorithm requires nothing but the active power measurement and some information about the households, it's suitable to be applied by a utility to provide an additional service to its residential customers.

REFERENCES:

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