Unsupervised algorithm for disaggregating lowsampling-rate electricity consumption of households

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Si cells with passivated contacts



Perovskite cells



Conductive oxides TCOs







PV grid integration and local storage



Advances coatings



Module design and reliability





DEVICE USAGE ESTIMATION ALGORITHM

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DLE POLYTECHNIQ

Residential NILM in unsupervised manner

Unsupervised

No training and time-consuming data collection

15 min data

Low-sampling rate of conventional smart meters

Efficient computing

Scales linearly with data growth





ASSUMPTIONS

- Children < 10 years old - no energy needs
- Teenagers < 18 years old -random activity chain
- Adults optimized activity chain
- No partial presence/absence at home





Start

Filter out

standby

Filter out fridae

Detect peak

End

CATEGORIES, APPLIANCES & ACTIVITIES

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	

Recognized activities:

- Clean
- Use computer
- Cook
- Wash dishes
- Eat
- Homework
- Play game
- Laundry
- Music
- Watch TV
- Shower
- Work

No appliances used:

- Sleep
- Outdoor

WORKFLOW



BENCHMARKING

Performance compared to state-of-the-art



COMPARISON SETTING

Algorithms

Datasets

ECO

- Combinatorial
 Optimization
- SMARTENERGY.KOM
- UK-DALE

Metrics

Error on energy share

$$E_m = \frac{\sum_t \hat{P}_m^t}{\sum_t \sum_m \hat{P}_m^t} - \frac{\sum_t P_m^t}{\sum_t \sum_{m \in M} P_m^t}$$

NMSE

$$\text{NMSE}_{m} = \frac{\sum_{t} \left(\hat{P}_{m}^{t} - P_{m}^{t} \right)^{2}}{\sum_{t} \left(P_{m}^{t} \right)^{2}}$$

Hidden Markov Model

Factorial

- Graph Signal Processing
- Discriminative disaggregation via sparse coding

RESULTS – ENERGY SHARE



- Average uncertainty on energy share ~ 20%
- DUE is unsupervised, while other are supervised
- DUE is survey-based, always assumes presence of all categories

RESULTS – NMSE



PV-lab

- Dataset dependent
- Acceptable deviation ≤2

CONCLUSION & OUTCOMES

DUE algorithm is...

- Unsupervised
- Based on 15-min data resolution
- Computationally efficient scales linearly with dataset size



Potential use:

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- For statistical applications
- By utilities to provide new services at low cost
- To be published soon





THANK YOU!

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