From domestic energy demand to household activity patterns





EPFL Outline

- Motivation
- Introduction
- Methodological approach
- Datasets and analysis
- To conclude



EPFL Motivation

- **Domestic energy usage** can be considered as being derived from the **activity patterns** of individuals inside the home (Rezvany et al. 2021).
- Domestic energy usage: energy used in residential buildings including electricity, heating, and hot water.
- As such an activity-based energy demand model that can create in-home energy usage profiles from household activity patterns is the key to a better building energy demand analysis.

EPFL Activity-based models (ABMs)

- Activity-based models portray how people plan their activities and travels over a period of time such as a day.
- This approach has been of **interest** to **transport modellers** as the demand for travel is assumed to be driven by participation in activities which are distributed in space and time.
- However, using ABMs in the domain of domestic energy demand research is still very limited and the human behaviour element is frequently neglected in the energy demand literature.

EPFL Activity-based energy demand scheme



5

EPFL High-level research question

High-level research question: "How can we simulate the domestic energy demand from household activity schedules from first principles?"



6

EPFL Research questions

- In order to achieve this high-level objective, we should answer the following research questions:
- 1. How to incorporate **in-home** and **out-of-home activity scheduling** in a **single** scheduling model with **intra-household interactions**? (Rezvany et al. 2023)
- 2. How can we create in-home energy usage profiles from household activity patterns?



EPFL A framework for joint simulation of in- and out-of-home activities, capturing intra-household interactions (Rezvany et al. 2023)



NR, TH, MB

From energy profiles to activity patterns

May 10, 2023

8

EPFL How can we create in-home energy usage profiles from activity patterns?

- Goal: find the relation between building energy usage and activity profiles
 - Ideal scenario: overlapping energy usage data with activity diary survey data
 - *Pragmatic scenario*: However, there is **no data** containing information on **both household activity schedules** and **energy usage**.
- BUT we have detailed data on building energy usage, as well as, detailed time-use-data, separately (no overlap between data).

EPFL How can we create activity patterns from in-home energy usage profiles?

- New goal: How do we use energy data to enhance existing activity models?
 - Add functionality to ABM model

NR, TH, MB

- Generate energy demand profiles
- Without having overlapping data to train it

- We looked in the literature to see if anyone tried to link energy and activity data to create a joint model.
- Now, however, there are parallels to similar problems in other contexts (e.g. detecting pedestrian activity patterns from WiFi signatures)

10

EPFL From Wifi traces to activity episodes

- Wifi traces are not accurate; either precise sensors with incomplete coverage or full coverage with imprecise sensors.
- As a result, data are **scarce**, **fuzzy**, or both.
- How this is relevant to our problem?
 - Cooking hob on → We do not know if they are doing another activity on the side (e.g. chopping food simultaneously)/ multiple people are helping in the cooking at the same time → not exact indication of the start and end time of food preparation process → Noisy representation of activity → need a joint probabilistic model

Appliance use ≠ Activity pattern



From energy profiles to activity patterns

EPFL A Bayesian approach to detect pedestrian destination-sequences from WiFi signatures (Danalet et al. 2014)

- Goal: extract the possible activity-episode sequences performed by pedestrians from digital traces in a communication network.
- Methodology: a Bayesian approach merges measured network traces and pedestrian semantically-enriched routing graph to compute the likelihood that a given sequence of activity episodes has actually generated the observed traces.
- Output: candidate activity schedules associated with the likelihood to be the true one.



EPFL Schematic view of our approach



EPFL Methodological approach

 A Bayesian approach merging the measured building energy profiles and semanticallyenriched activity-related energy demand profiles to compute the likelihood that a given sequence of activity episodes has actually generated the observed energy profiles.

EPFL Schematic view of our approach



EPFL Datasets

Energy dataset

Intelligent Domestic Energy Advice Loop (IDEAL)

(Pullinger et al., 2021; Goddard et al., 2021)

- Comprises data from 255 homes in Edinburgh and the nearby regions.
- Collected over a 20-month period between August 2016 and June 2018.
- Enhanced appliance-level energy monitors in 39 of 255 homes.



Time use survey

CaDDI* survey - 2016-2020 UK TUS

(Gershuny and Sullivan, 2021)

- 4'360 diaries from 2'202 individuals across 4 waves
- 4 waves (2016 & late May-June, August, November 2020)
- Contains 1 to 3 time-use diaries per respondent (include 1 weekday and 1 weekend day)
- Includes information on socio-demographic variables, activities, location, enjoyment, and co-presence



EPFL Exploration of data: Appliance energy profiles



NR, TH, MB

From energy profiles to activity patterns

May 10, 2023

EPFL Exploration of data: Appliance energy profiles



 \rightarrow looking for a set of patterns and rules...

NR, TH, MB

From energy profiles to activity patterns

EPFL Exploration of data: Ambient light-level vs energy profiles

Electricity usage – cooking hub:



NR, TH, MB

From energy profiles to activity patterns

May 10, 2023

EPFL Exploration of data: Parallels at aggregate level

Distribution of "Preparing food/cooking" activity:





20

NR, TH, MB

From energy profiles to activity patterns

May 10, 2023

EPFL Exploration of data: Parallels at aggregate level



EPFL To conclude

Summary:

- Joint model of domestic energy and activity profiles
- Recreate household activity patterns from domestic energy usage profiles
- Non-overlapping data
- Probabilistic model Bayesian approach

- Danalet, A., B. Farooq and M. Bierlaire (2014) A Bayesian approach to detect pedestrian destination-sequences from WiFi signatures, Transp. Res. Part C Emerg. Technol., 44, 146–170, ISSN 0968090X.
- Gershuny, J. and O. Sullivan (2021) United Kingdom Time Use Survey Sequence Pre and During COVID-19 Social Restrictions.
- Goddard, N., J. Kilgour, M. Pullinger, D. Arvind, H. Lovell, J. Moore, D. Shipworth, C. Sutton, J. Webb, N. Berliner, C. Brewitt, M. Dzikovska, E. Farrow, E. Farrow, J. Mann, E. Morgan, L. Webb and M. Zhong (2021) IDEAL Household Energy Dataset [dataset].
- Pullinger, M., J. Kilgour, N. Goddard, N. Berliner, L. Webb, M. Dzikovska, H. Lovell, J. Mann, C. Sutton, J. Webb and M. Zhong (2021) The IDEAL household energy dataset, electricity, gas, contextual sensor data and survey data for 255 UK homes, Sci. Data.
- Rezvany, N., T. Hillel and M. Blerlaire (2021) Integrated models of transport and energy demand : A literature review and framework, paper presented at the Swiss Transp. Res. Conf., no. September, Ascona, Switzerland.
- Rezvany, N., M. Bierlaire and T. Hillel (2023) Simulating intra-household interactions for in- and out-of-home activity scheduling, Technical Report.



