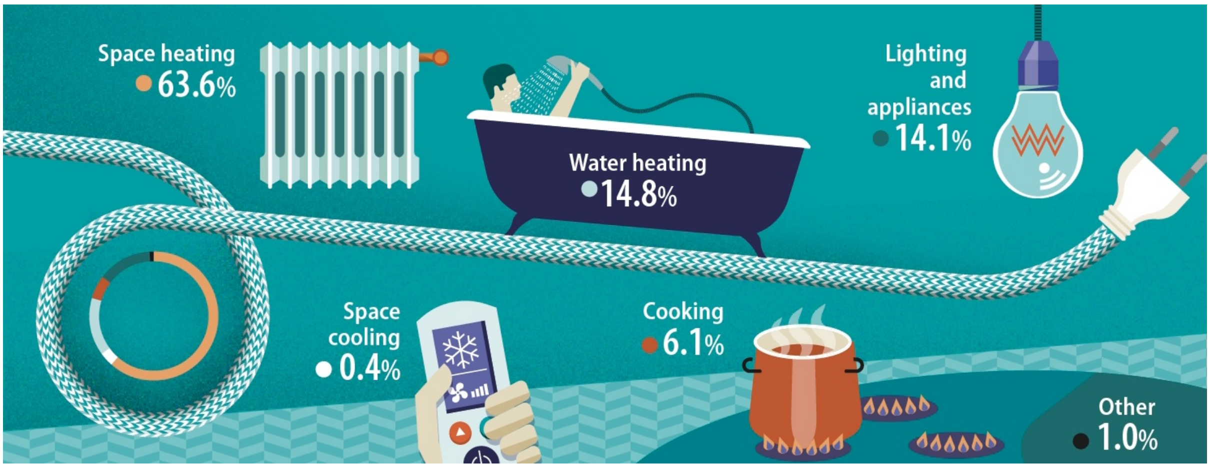

From domestic energy demand to household activity patterns

Negar Rezvany

Tim Hillel

Michel Bierlaire

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From domestic energy demand to household activity patterns

Negar Rezvany
Transport and Mobility Laboratory (TRANSP-OR)
École Polytechnique Fédérale de Lausanne (EPFL), Switzerland
negar.rezvany@epfl.ch

Tim Hillel
Department of Civil, Environmental and Geomatic Engineering
University College London (UCL), United Kingdom
tim.hillel@ucl.ac.uk

Michel Bierlaire
Transport and Mobility Laboratory (TRANSP-OR)
École Polytechnique Fédérale de Lausanne (EPFL), Switzerland
michel.bierlaire@epfl.ch

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Abstract

Residential building energy usage can be considered as being derived from the activity patterns of individuals inside the home. 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. In order to find the relation between building energy usage and activity profiles, energy usage data with an overlapping activity diary survey is needed. However, there is no detailed data containing information on both household activity schedules and energy usage. Therefore, utilizing a Bayesian approach, we explore the possibility of reverse engineering to get the household activity patterns from energy usage profiles. The findings can be further used for linking the domestic energy demand to the activity schedules of the occupants.

Keywords

Activity-based energy demand analysis, Activity-based modelling, Building energy usage data.

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1 Introduction

Residential building energy and transport demand can both be considered as being derived from the activity patterns of individuals. As such, both are inherently linked: participating in activities inside the home generates domestic energy demand, and completing activities outside the home, with consecutive activities at different locations, generates transportation demand. Therefore, understanding and predicting complex behaviour and interactions throughout the day is the key to better demand-side management and adapting infrastructure systems (e.g. transportation, energy) to deliver critical services that meet the needs of society.

Activity-based models (ABMs) 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 (Hilgert *et al.*, 2017; Bhat *et al.*, 2004; Bowman and Ben-Akiva, 2001; Axhausen and Gärling, 1992; Chapin, 1974; Hagerstrand, 1970). These models try to replicate the actual decisions of travellers with more behavioural realism compared to the traditional trip-based models. 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 (Sovacool *et al.*, 2015).

We consider an alternative approach to building energy demand modelling, by coupling residential building energy demand to the activity patterns of its inhabitants. Therefore, we get a high-level research question: "How can we simulate the domestic energy demand from household activity schedules from first principles?" This extends the activity-based modelling paradigm to residential building energy demand. 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?
2. How to model household activity schedules accounting for intra-household interactions that affect individuals' activity scheduling?
3. How can we create in-home energy usage profiles from household activity patterns?

In order to address the first two questions, we propose a framework that jointly simulates in- and out-of-home activities and incorporates multiple interactions into a single activity-based model. We reconstruct the daily activity schedules of individuals in the same household, considering both the individual- and household-level needs, preferences, and constraints. The model explicitly accommodates complex interactions among household members such as the allocation of the private vehicle to household members, escort duties, joint participation in activities, and sharing rides. The framework is published as a technical report (Rezvany *et al.*, 2023) on the TRANSP-OR website. The paper is submitted to a journal and is under review for publication.

In order to address the third question, detailed building energy data containing information on activity schedules is needed. However, no such dataset containing overlapping data on household activity diaries and building energy demand exists. Therefore, we explore the possibility of reverse engineering to get the household activity patterns from energy usage data. We can then use the findings for linking the domestic energy demand to the activity schedules of the occupants. Thus, the aim of this paper is specifically to investigate the following questions:

1. How can we get from domestic energy usage sensor data to appliance usage?
2. How can we relate appliance usage to activity patterns?
3. How can we create household activity patterns from domestic energy usage profiles?

By recreating individuals' activity schedules in a day from the domestic energy demand, our research sets the ground truths to address the primal research question; how can we go from in-home activity schedules to domestic energy demand patterns. The research plan is presented in this manuscript.

2 Research plan

2.1 Overview

We go from domestic energy demand to activity schedules, aiming at connecting the energy usage data to their corresponding high-level household activity patterns. Using data containing household energy and appliance usage, we can couple the appliance usage to their corresponding energy usage data collected from sensors. The high-level activity patterns of the household can be then approximated from appliance and energy usage. Therefore, finally, we can join the household activity patterns with their corresponding building energy demand. For this purpose, we use a detailed household domestic energy dataset from the United Kingdom (UK), described in the following section.

2.2 Dataset

In order to understand the relationship between the households' activity patterns and their corresponding energy and appliance usage, we make use of a detailed UK household energy data, called Intelligent Domestic Energy Advice Loop (IDEAL) dataset. A UK time use diary survey data has also been identified for empirical analysis of individuals' daily activity patterns. It is notable that, as there is no overlap between the time-use diary and energy usage data, the Time use survey (TUS) would only be used as an indicative of typical activity patterns of individuals in the UK, but cannot be directly used for linking the two domains.

2.2.1 Activity diary data

The data from the UK TUS (Gershuny and Sullivan, 2021) is used for empirical analysis of individuals' activity patterns. This dataset includes information on respondents' socio-economic characteristics and those of their household, as well as detailed diary information on activity, location, accompaniment, and household appliance ownership. The $2016 - 2020$ survey contains 4360 time-use diaries with 10-minutes time resolution, from 2202 respondents. The data is collected in four waves among which the last three waves have been collected during the COVID-19 pandemic. To ensure sufficient diversity in schedules, we use only the data collected before the COVID-19 pandemic in 2016, which contains 1011 surveys from 659 respondents.

2.2.2 Energy usage data

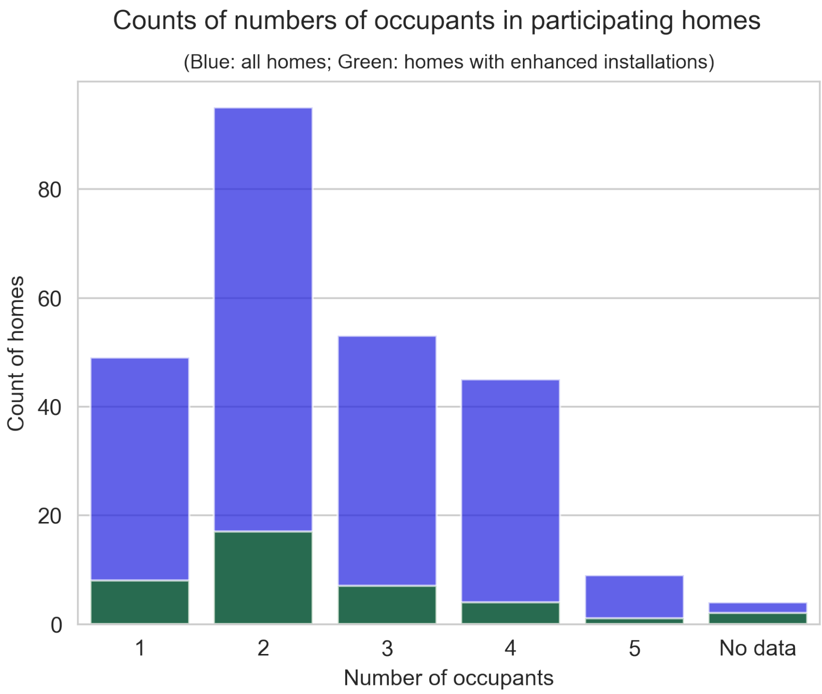
The IDEAL Household Energy Dataset (Pullinger *et al.*, 2021; Goddard *et al.*, 2021) comprises data from 255 homes in Edinburgh and the nearby regions of the Lothians and South Fife in Scotland, UK, collected over a 20-month period between August 2016 and June 2018. There are varying start and end times of participation, with homes having a mean duration of 286 days over this period.

It contains electric and gas sensor data from each home along with a diverse range of relevant contextual data from additional sensors and surveys. The data contains metadata describing houses and their household members, as well as, time-series sensor data from individual sensors in the houses. Sensor monitoring in all homes includes 1-second apparent-power electricity data, pulse-level gas data, 12-second temperature, humidity and light data for each room, and 12-second measurements of boiler pipe temperatures to indicate usage of central heating and hot water. Also, a survey data collected from participants at several times during the study reports repeated measures of environmental attitudes of participants as well as their socio-economic characteristics such as age and working status.

For 39 of the 255 homes, more detailed data is available through an enhanced sensor system installed, such as individual electrical appliance use data (electricity usage and time of use), and more detailed temperature monitoring of gas- and heat-using equipment, including radiators and taps. Sensor data is augmented by anonymised survey data and metadata including occupant demographics, self-reported energy awareness and attitudes, and building, room and appliance characteristics. It is notable that participants have gone through an eligibility check for the data collection in order to reduce certain sources of variability in home energy usage which complicate the analysis of the data and development of energy advice.

Figure 1 presents the distribution of household size in the dataset.

Figure 1: Distribution of number of occupants in the participating homes



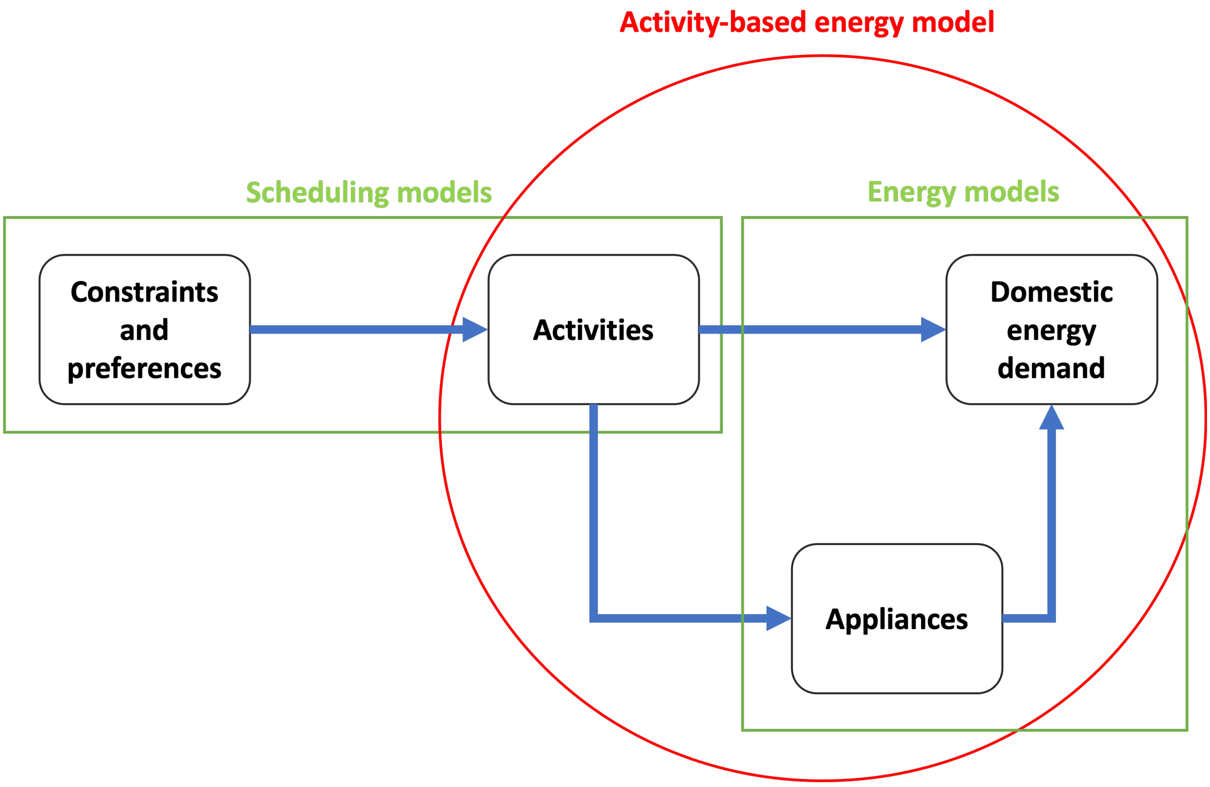
Data on the following variables and demographics are reported in the IDEAL dataset:

- Sensor data: energy use (overall and by selected appliances), indoor temperature, humidity and light levels,
- Self-reported comfort and satisfaction,
- Socio-demographic characteristics,
- Household dynamics,
- Energy information and awareness, and
- Weather conditions.

2.3 Methodological approach

Figure 2 presents the relation between activity and energy usage patterns. Individuals plan their day based on a set of constraints and preferences. This is of interest to activity-based modellers and is addressed in scheduling models. The in-home activities contribute to domestic energy usage either through appliance usage or through building occupancy affecting baseline building energy usage such as space heating. Energy demand models study the link between appliance usage and domestic energy demand. However, there are no activity-based energy models linking domestic energy demand to activity patterns. As there is no detailed data containing information on both household activity schedules and energy usage, we consider a reverse approach to this existing gap and thus, explore getting the household activity patterns from energy usage data (Figure 3).

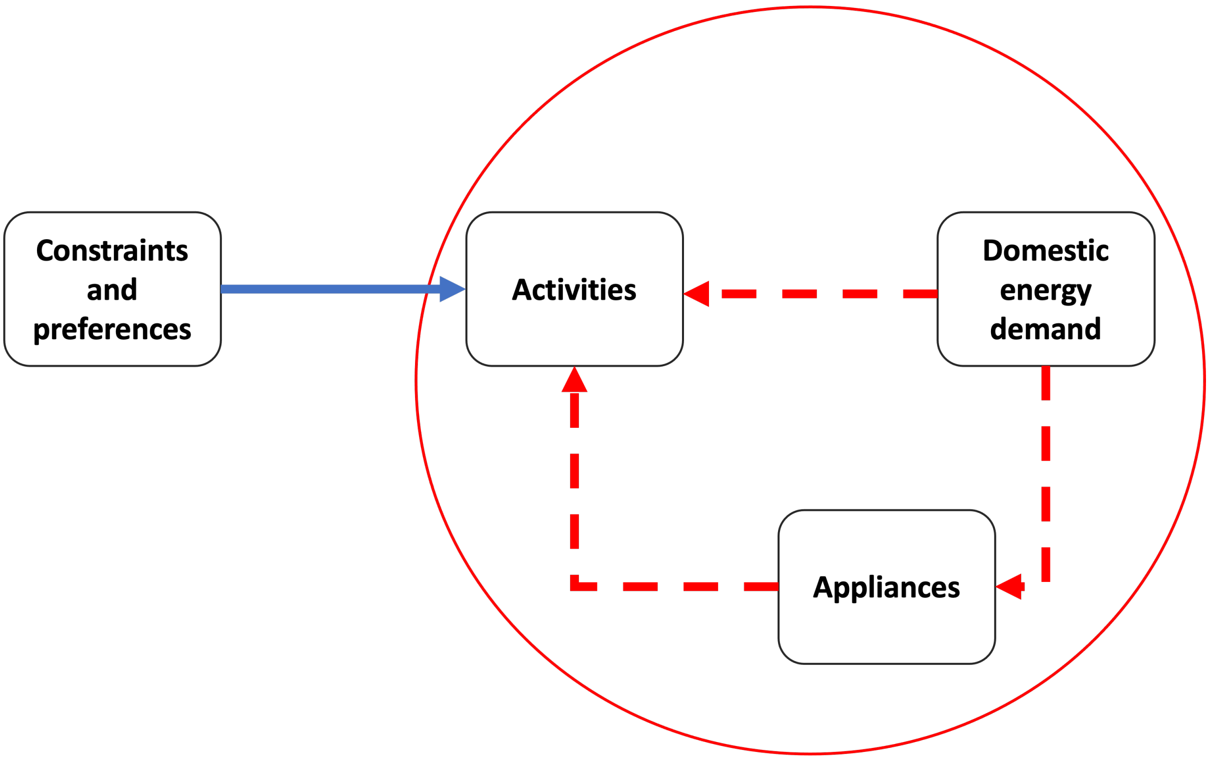
Figure 2: Forward path approach



The domestic energy demand is caused either by appliance usage for activities completed at home such as cooking, showering, hoovering, and laundry, or by the baseline building energy usage such as lighting, hot water, space heating and cooling, ventilation, and air-conditioning which are indirectly dependent on the household in-home activity schedules through the building occupancy. There are also appliances running in the background regardless of activities and building occupancy such as fridges and freezers.

By the analysis of the IDEAL energy dataset, we can estimate the usage patterns of appliances from the available enhanced sensor data, which reports the time-series energy usage of selected appliances. Furthermore, the reported time-series on heating/cooling and lighting levels for each room can be used for estimating the room and building occupancy; whether any household member is at home and if so, in which room(s). For example, from the corresponding energy and lighting data of the bathroom, we can realise when a household member is taking a shower. Or similarly, from the heating and lighting data of the bedroom, the occupants' sleeping time patterns can be approximated. Likewise, the building occupancy; whether an occupant is at home or is doing an activity at an out-of-home location can be estimated from the domestic energy and lighting profile. Therefore, utilizing a Bayesian approach, we can obtain the household activity patterns using appliance use patterns as well as energy usage and lighting levels. Figure 3 presents a scheme of this reverse approach. This should support further work looking into Bayesian modelling of household energy and heating demand from activity patterns.

Figure 3: Our current reverse approach



3 To conclude

This manuscript presents a research plan to recreate household activity patterns from domestic energy usage profiles. Utilizing a Bayesian approach, we link the two domains of activity and building energy usage through the analysis of a detailed household energy dataset. This should support further work looking into Bayesian modelling of household energy and heating demand from activity patterns.

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