Integrated in- and out-of-home scheduling framework: A utility optimization-based approach

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Abstract

Existing activity-based modeling predominantly focus on out-of-home activities in order to understand transport demand. In this research, we extend the state of practice in activity-based modelling by determining both in- and out-of-home activities in a single scheduling framework. This approach has two main benefits: Firstly, it can capture the trade-offs between in-home and out-of-home activities. Secondly, in-home time-use patterns can be used to model high resolution energy demand.
Our work builds on an existing optimisation framework, which treats individuals as maximising their total utility from completed activities and incorporates multiple scheduling decisions simultaneously. The approach is tested on a set of detailed daily schedules extracted from the the 2016-2020 UK Time Use Survey data.
The results show that the model is able to generate peoples' daily activity schedules based on their individual preferences and constraints.

Keywords: Activity-based modeling; Daily scheduling behavior; Transport demand; Energy demand; Mixed-integer optimization; Time use survey data.

1. INTRODUCTION

Out of home activity participation has been modeled extensively for activity-based transport models in the last decades. These models derive travel demand from agents' participation in activities distributed in space and time (Axhausen & Gärling, 1992). There are two major research streams within the scope of activity-based models among transport modelers: (i) empirical rule-based such as (Golledge, Kwan, & Garling, 1994; Arentze & Timmermans, 2000) that rely on the assumption that decision-makers consider conditional rules and heuristics to make decisions, and (ii) econometric utility-based such as (Adler & Ben-Akiva, 1979; Bowman & Ben-Akiva, 2001) that are based on the assumption that individuals choose their activity schedule to maximize the utility they gain from it. Travel behavior is modelled as a result of discrete choices, treated sequentially, and solved with econometric methods such as advanced discrete choice models (Bowman & Ben-Akiva, 2001; Nurul Habib & Miller, 2009) or microsimulation (e.g., STARCHILD (Recker, McNally, & Root, 1986), CEMDAP (Bhat, Guo, Srinivasan, & Sivakumar, 2004)).

However, these existing scheduling approaches in the literature have generally two shortcomings (Pougala, Hillel, & Bierlaire, 2021):

1. They are either hard-coded and cannot be generalised to situations not seen in the data, or
2. They do not represent the nature of scheduling process and cannot capture complex trade-offs and household interaction.

In order to address these shortcomings, Pougala et al. (2021) proposes a new optimization-based scheduling framework based on first principles which integrates different scheduling choice dimensions simultaneously. This approach treats individuals as maximising their total utility from completed activities in order to schedule their day and incorporates multiple scheduling decisions such as activity participation, activity scheduling, and location choice simultaneously. One of the major advantages of this framework is its high level of flexibility. This flexibility would allow the framework to model both in-house and out-of-house activity participation in the same optimsiation problem. However, so far this framework has been applied only for out-of-home activity scheduling (developed for transportation models), and the resulting schedules do not contain any information on activities performed at home.

This leave us a gap to extend the state of practice by jointly modelling time-use in the alongside activity participation outside the home. This information can serve two primary purposes:

- The time-use pattern inside home can be used to predict building energy demand at high temporal resolution. Energy and transport demand can both be considered as being derived from an individual's activity participation. As such, activity scheduling is the connecting element between transportation and energy simulation. A comprehensive literature review and a proposed framework for integrated models of transport and energy demand is discussed in a paper by Rezvany, Hillel, and BIerlaire (2021).
- It allows modellers to capture the trade-offs between in-home and out-of-home activities. This is of high relevance for capturing the impact of flexible home-working policies. With the COVID-19 pandemic, the lifestyle and behavior of people have changed dramatically. Activities which were traditionally done out-of-home (such as work and education), are now more likely to take place in-home and remote working and studying has become an integral part of our lives. Combining in-home and out-off-home scheduling in the same modelling can provide unique insights into how individuals schedule activities throughout

the day in the post-COVID era.

To achieve this, we build on the existing optimization-based scheduling framework of Pougala et al. (2021) to incorporate time-use for activities in the home (e.g., sleeping, cooking, showering, etc). This approach is validated on daily schedules extracted from Time Use Survey (TUS) data.

The remainder of this manuscript is structured as follows. Section 2 introduces the scheduling model framework used in this research. In the Section 3, an empirical investigation consisting data preprocess and model assumptions are presented. Results are presented in Section 4. Finally, the concluding remarks and future research are presented in Section 5.

2. Model Framework

In this study, we build on the scheduling model developed by Pougala et al. (2021) to incorporate join modelling of time-use in the home alongisde activities outside the home. This extended framework can be applied to full daily schedules extracted from TUS data.

The framework treats individuals as utility maximizers. The problem is defined as a mixed-integer optimization problem for each individual, maximising the sum of the utilities of completed activities in a schedule over a fixed time budget. It incorporates a simultaneous estimation of multiple scheduling decisions such as activity participation and activity scheduling (start time, duration, sequence). The framework is defined under a set of constraints which define the time budget, location, duration, sequence, and time window constraints. The model takes as input a set of activities with associated location. The framework defines a distribution over possible schedules and stochastically draws likely schedules from a distribution for a given individual. The output of the model is a feasible schedule S. As the utility functions of all activities depend on the error term, we expect different draws of the error term to generate different solutions.

For a comprehensive explanation of the model, including a complete formal definitions of model constraint and parameters, we direct the reader to Pougala et al. (2021).

We introduce a minimum duration of 10 minutes for the activities, reflecting the high-resolution nature of in-home time use patterns.

3. Empirical Investigation

In order to show the capability of the modeling framework on a real-world case-study, we have make use of data from the UK 2016-2020 TUS. The data is first preprocessed to extract the necessary schedule information and present them in the format compatible with the model. This is presented in section 3.1 We make realistic assumptions to provide estimators for the missing attributes in the current dataset and simplify the model at this stage (section 3.2).

3.1. Data preprocess

The UK 2016-2020 TUS (Gershuny & Sullivan, 2021) has been used as an input to the model. The data collection of this time use diary has been conducted in four waves among which the last three waves have been collected during the COVID-19 pandemic (late May-June (full lockdown), August (during the easing of social restrictions), and November (second lockdown) 2020). Therefore, this dataset provides information to compare the behavioural changes between pre-COVID, COVID lockdown, and the intervening period of the relaxation of restrictions. This survey contains 4360 time use diaries in which people were asked to list, in sequence, all the things they have done, with the start and end times of each successive activity, from 4 AM until 4 AM of the next day. It contains between one to three time-use diaries per respondent to include one weekday and one weekend day. The survey consists of individual questionnaires including information on socio-demographic variables, household equipment, device use, preferences and satisfaction, effects of lockdown, and diary information on activity, location, and accompaniment.

In this study, we extract an individual's activity diary for a single day, including activity start and end times and duration, alongside their location in space (given accurate to 10 minutes time intervals). We then covert the schedules to Pandas DataFrame in order to use them as an input to the model to simulate new feasible schedules.

3.2. Modeling assumptions

Activity flexibility assumption: We have classified the activities in the UK TUS data into different categories; mandatory, maintenance, and discretionary. Mandatory activities refer to activities which are the least flexible and will be penalized the most if deviated from the preference such as work and study activities. Maintenance activities refer to service-related activities and personal or household needs such as meal preparation. This category is more flexible compared to the mandatory activities regarding start and duration deviations. Discretionary activities refer to the activities related to recreation, sports, civic services, and social visits. Activities in this category have high start and duration flexibility. As the required inputs to the model are not all available in the survey, we have made some realistic assumptions and have provided some heuristics to estimate the missing attributes including feasible start, feasible end, and flexibility profiles.

Different activities have different levels of flexibility towards starting and duration deviations from the preferred one and thus, are penalized to different extents. This can be shown using three levels of flexibility (Pougala et al., 2021):

1. **Flexible (F)**: deviations from preferences for activity i are relatively unimportant, thus are less or not penalized.
2. **Moderately flexible (MF)**: deviations from preferences are moderately undesirable, and so are more penalized than in the flexible case.
3. **Not flexible (NF)**: deviations from preferences are strongly undesirable, and are highly penalized.

Table 1 shows the flexibility profiles of different activity categories in the UK TUS survey data. Each activity category is associated with a flexibility level and each level of flexibility is characterised by specific penalty values. At this stage of the model, for the sake of simplicity, the values associated to each flexibility level are deterministic and homogeneous across the population. The penalty values are chosen according to the literature (Pougala et al., 2021). As presented in the table, mandatory activities are less flexible in start time and duration compared to the other groups.

Travel time assumption: In the UK survey data, we only know the generic location of the activity out of *home*, *work*, or *other place*, and do not have the geographical coordinates of the locations of activities from which accurate travel times could be calculated. Therefore, at this stage of the research, we have made the following simplifying assumption: if the location of two consecutive activities are not the same, the travel time between the two locations is a fixed amount of 0.25 hr accounted in the activity duration.

Table 1: Categories and flexibility profiles for activities in the UK TUS

Activity	Category	Start flexibility	Duration flexibility
Paid work Formal education	Mandatory	Early:NF Late:MF	Short:NF Long:NF
Maintenance daily Consuming services Caring for own child Caring for other children Help, caring for core adult Help, caring for non-coresidents Voluntary work for organisation Shopping, bank incl internet Cinema, theatre, sport Preparing food, cooking Washing, dressing Cleaning tidying housework Clothes washing and mending Sleeping Resting Eating, drinking	Maintenance	Early:MF Late:MF	Short:MF Long:F
Reading Recreational courses Playing sports,exercise Going out to eat, drink Walking, dog walking Playing computer games Time with friends and family Telephone, text, email, letters Hobbies Church, temple, synagogue, prayer Work and study break Watching TV, video, DVD, music	Discretionary	Early:F Late:MF	Short:F Long:F

4. Results and discussion

The following analysis is performed on a single schedule taken from the UK TUS data, which presents the schedule of a given day for a given person. The chosen schedule is visualized in Figure 1. We use this given schedule as an input to the scheduling model. The activity start time and duration preferences are assumed to be the ones considered in the given schedule from the data.

Figure 2 presents 5 outputs of the model, which are random draws from the feasible distributions of schedules generated from different draws of the error term.

As seen in the model solutions, mandatory activities such as paid work are less flexible. Therefore, we can see that we have paid work in all the simulated schedules. This is while maintenance activities such as caring for children are more flexible and have less penalty if deviated from preference or not scheduled at all. So, we can see that they might not be present in all the simulated schedules.

We can see in the model results that in some realizations of the simulation, we have the eating activity in nearly two consecutive time slots with no eating during the rest of the day, or sometimes have only one meal during the day. These might at first seem unusual but, there is a probability for such schedules in daily schedules. For example, we might skip some meals when having busy working days or we might skip some meals because we had a heavy meal earlier.

Our contribution in this paper is modeling the in-home activities in addition to the out-of home activities utilizing the scheduling model developed by Pougala et al. (2021) which was modeled and utilized for only the out-of home activities and travels utilizing travel diary survey data. This information can serve for two primary purposes: first, the time-use pattern inside home can be used to predict building energy demand at high temporal resolution. Second, with this information, we can capture the trade-offs between in-home and out-of-home activities. This is of high relevance specially in the post-COVID era such as capturing the impact of flexible home-working policies. As results show, we can use this scheduling approach to jointly model the time-use in home as well as the activities outside home, making use of TUS data. An important part of this study was the data preprocess in order to derive the information needed in the model and in the format compatible to the model.

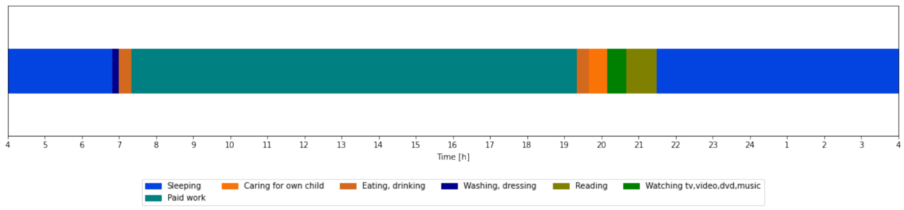

Figure 1: Original schedule

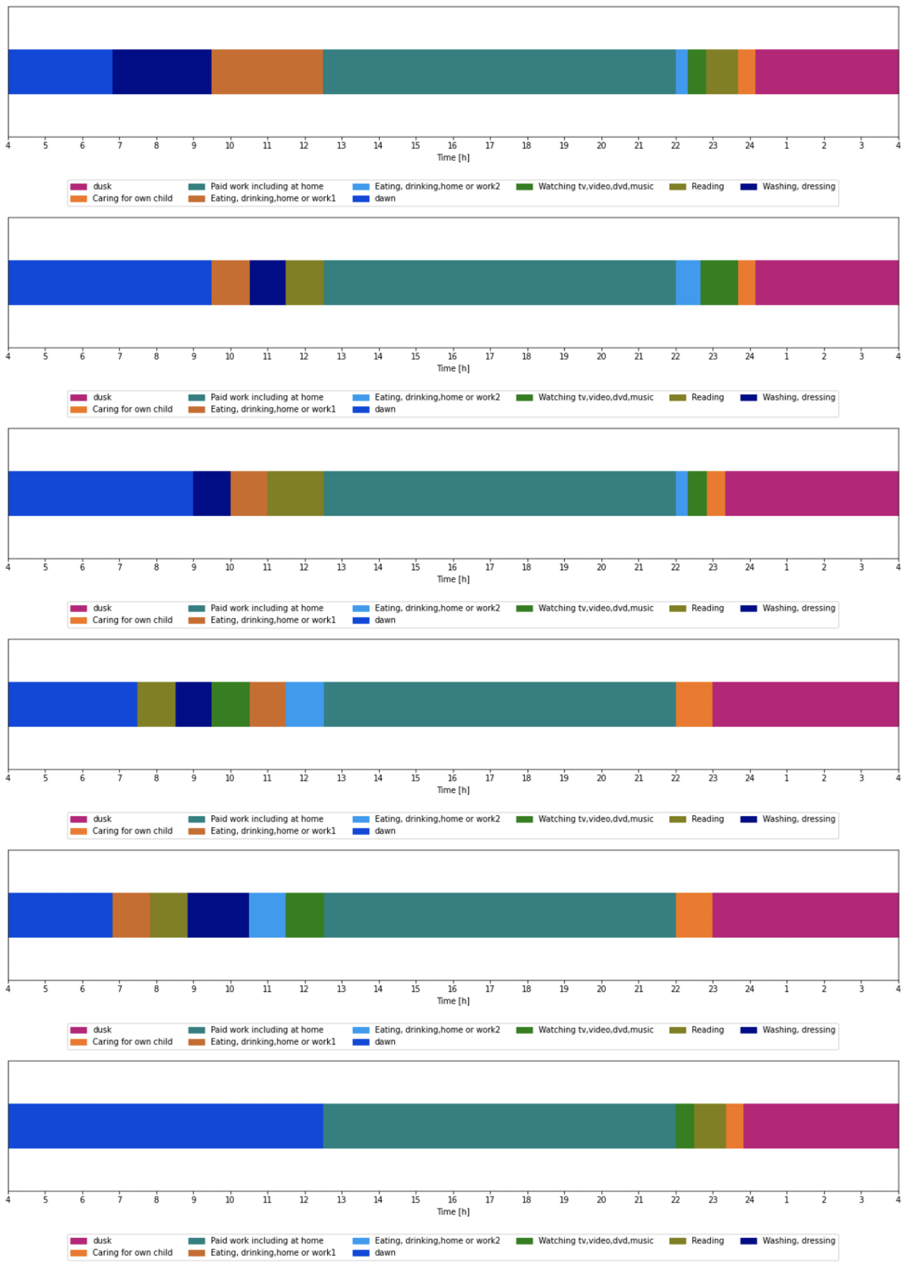

Figure 2: Model solutions

5. Conclusions and Future Work

In this paper, we have proposed a new viewpoint on activity scheduling of individuals. The main contribution of our research is the application of the utility maximization approach based on first principles, which was originally developed for simulation of only out-of-home activities in activity-based transportation simulation, to jointly model in-home activities as well.

Out of home activity participation has already been modeled extensively for transport demand modeling in form of activity-based transport models in the last decades. However, although behavior is the key element joining mobility and energy use, the human behavior element is frequently neglected in the energy demand literature (Sovacool et al., 2015) and the current energy demand models are mostly based on active occupancy concept. There is therefore limited understanding of the interactions between these sectors. In order to address this gap, we propose an integrated model of disaggregate energy and transport demand using activity-based approach to model complex individual behaviors due to the multiplicity of individual actors, their multi-criteria objectives, and the multidimensionality of relevant factors. By recreating individual activity schedules in a day, our research proposes an integrating framework to co-simulate and study the interdependencies of energy demand and transport modeling. This new modeling paradigm, can be used to directly model both energy demand and transport demand derived from in-home and out-of-home activity participation.

One major limitation of the current implementation is that the agent currently considers only activities completed in the original schedule. As such, the resulting schedules from the optimisation approach can only either the activities already completed, or a subset of these activities. A key step for future work is to include a choice set generation model, in which alternatives that were not already chosen by the considered agent can be included. Other key directions for future works also include the modification of the model to account for location choice for work and education activities and the trade-off between conducting activities in- and out-of-home. The out-of-home activity locations have the advantage/disadvantage of social interaction for a sociable/unsociable person compared to in-home location (only the limited interaction with members of the household). For this purpose, we aim to use the data regarding the enjoyment level of activities in the UK TUS data in order to have an understanding of the sociability characteristic of the individual and then, estimate the location choice parameter accordingly. Also, in the next steps of this research, we will estimate the values of parameters in the model from the data.

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