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 and applications: 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, which can contribute to demand side management.
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 framework has been extended to determine the choice of location for activities such as work, study, and leisure. The approach is tested on a set of detailed daily schedules extracted from 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 preferences and constraints.

Keywords

Activity-based modeling; Daily scheduling behavior; Mixed-integer optimization; Time use survey

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1 Introduction

1.1 Motivation

Daily scheduling of individuals has been of interest for activity-based transport modelers as the demand for travel is assumed to be driven from agents' participation in activities distributed in space and time (Axhausen and Gärling, 1992). Out-of-home activity participation has been modeled extensively for activity-based transport models in the last decades (e.g., Bowman and Ben-Akiva 2001; Vovsha *et al.* 2004; Bhat *et al.* 2004; Hilgert *et al.* 2017). However, modeling all the daily activities (including both in- and out-of-home activities) within the same scheduling framework has not been addressed in the existing literature. Therefore, the interactions between in- and out-of-home activities (e.g., squeezing in-home activities when spending more time on out-of-home activities, deciding where to do different activities; in-home or an out-of-home location; based on the schedule of the whole day) are missing in the current studies.
In this research, we extend the state of practice in activity-based modeling by determining both in-and out-of-home activities within the same scheduling framework. The novelty of this research is the application of the activity-based modeling approach, which has been well-understood among transport modelers, within a new context; how individuals schedule their activities through the *entire* day.
This modeling approach can contribute to demand side management, where understanding how people schedule their activities throughout the entire day is needed.

1.2 Related studies in the literature

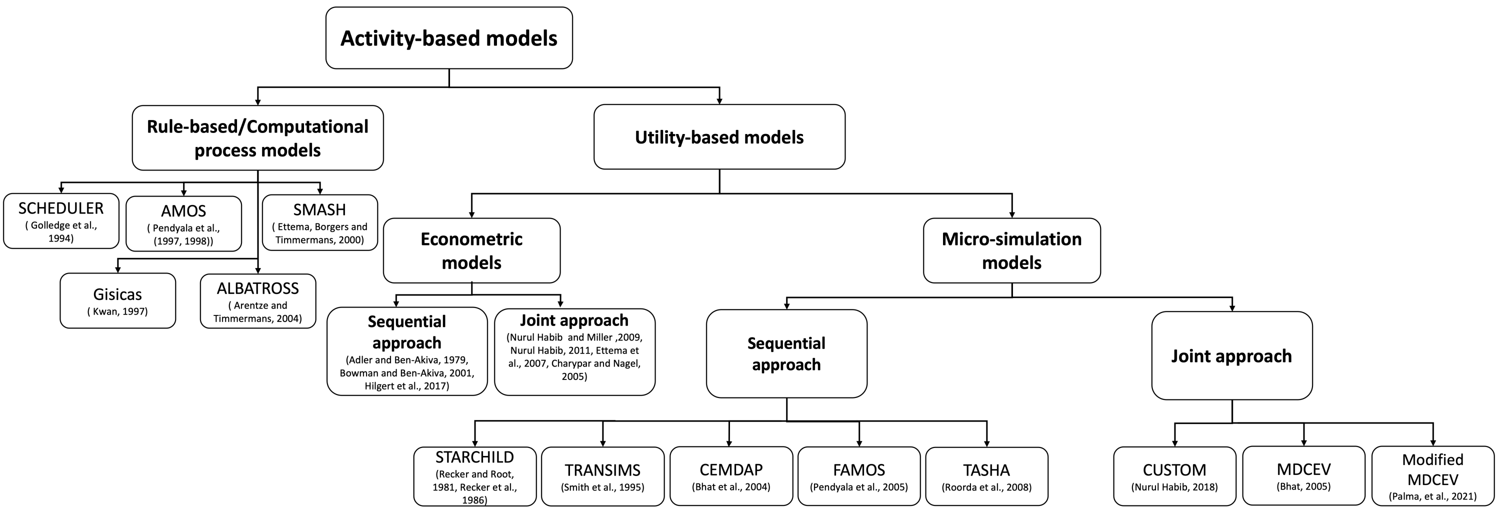
There are two major research streams within the scope of activity-based models among the transport modelers:

(i) empirical rule-based/computational process models such as the studies by Golledge *et al.* (1994); Kwan (1997); Pendyala *et al.* (1997, 1998); Ettema *et al.* (2000); Arentze and Timmermans (2004), that rely on the assumption that decision-makers consider conditional rules (IF...THEN...ELSE rules) and context-dependent heuristics to make decisions and form their activity patterns.

(ii) utility-based models that are based on the assumption that individuals choose their activity schedule to maximize the utility they gain from it subject to a set of constraints. Travel behavior is modelled as a result of discrete choices, mostly treated sequentially, and solved with econometric methods such as advanced discrete choice models (Adler and Ben-Akiva, 1979; Bowman and Ben-Akiva, 2001; Charypar and Nagel, 2005; Ettema *et al.*, 2007; Nurul Habib and Miller, 2009; Nurul Habib, 2011; Hilgert *et al.*, 2017) or microsimulation models (e.g., STARCHILD (Recker and Root, 1981; Recker *et al.*, 1986), TRANSIMS (Smith *et al.*, 1995), CEMDAP (Bhat *et al.*, 2004), FAMOS (Pendyala *et al.*, 2005)), TASHA (Roorda *et al.*, 2008), CUSTOM (Nurul Habib, 2018), MDCEV (Bhat, 2005), and Modified MDCEV (Palma *et al.*, 2021)).

Figure 1 classifies the existing research streams within activity-based models and presents some of the relevant models in the literature.

Figure 1: Research streams within the scope of activity-based models



However, these existing scheduling approaches in the literature have generally two shortcomings (Pougala *et al.*, 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 interactions.

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 and scheduling 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 optimisation problem. However, so far this framework has been applied only for studying the 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 home alongside activity participation outside the home.

1.3 Objectives and contributions

We build on the existing optimization-based scheduling approach of Pougala *et al.* (2021) to incorporate time-use for activities in the home (e.g., sleeping, homecare) in addition to the activities performed out of the home. The modeling framework is operationalized using daily schedules extracted from Time Use Survey (TUS) data. The information from joint modelling of in- and out-of-home time use can serve for two primary purposes:

- 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. Jointly modeling in-home and out-of-home scheduling within the same framework can provide unique insights into how individuals schedule activities throughout the day in the post-COVID era.
- 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. Thus, understanding the activity scheduling behavior of individuals highly contributes to demand side management. A comprehensive literature review and a proposed framework for integrated models of transport and energy demand is discussed in a

paper by Rezvany *et al.* (2021).

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 pre-process and model assumptions are presented. Results are discussed 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 approach developed by Pougala *et al.* (2021) to incorporate joint modeling of time-use in the home alongside activities outside the home. This extended framework can be applied to simulate full daily schedules.

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. The objective function is as follows:

$$\Omega = \max \sum_{i} \omega_{i_n} U_{i_n} \tag{1}$$

where ω_{i_n} is a binary variable indicating participation in activity i for individual n and is equal to 1 if activity i is scheduled and 0 otherwise. U_{i_n} is the utility that individual n gains performing activity i, which can be either positive, negative, or zero.

This approach 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, feasible time window, activities duration, and sequence constraints. The model takes as input the a set of possible activities, locations, travel time matrix, scheduling preferences, activity flexibility profiles, penalty values for deviations from the preference, and feasible time windows. The framework defines a distribution over possible schedules from which likely schedules can be stochastically drawn. The output of the model is a feasible schedule. For a comprehensive explanation of the model, including a complete formal definitions of model constraints, parameters, and its mathematical formulation we direct the reader to the technical report on the model by Pougala *et al.* (2021).

We have applied the following modifications and extensions to the model:

1. **Minimum activity duration of 10 minutes**: We introduce a minimum duration of 10 minutes for the activities, reflecting the high-resolution nature of in-home time use patterns.
2. **Activity location choice**: We have extended the model to account for location choice for work, education, personal care, and leisure activities. With the emergence of the pandemic, we have observed that many activities which were traditionally conducted out-of-home are considered to be done at home or online. Conducting activities at home has the advantage of saving time on traveling. We have considered the location choice options of 'Home' or 'Work' for work activities, and 'Home' or 'Other' for education, personal care, shopping, and leisure activities. It is notable that in the current model, the only utility difference between in- and out-of-home activity locations is the travel time. However, 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) as well. This is one of the possible extensions to address in future research.

3 Empirical investigation

In order to show the capability of the modeling framework on a real-world case-study, we have showcased the framework on the data from the UK 2016-2020 TUS. The data is first pre-processed to a layout compatible with our modeling needs and then the required data and model requirements are derived from it. The pre-processing steps are presented and discussed in Section 3.1 At this stage of the research, we have made realistic assumptions to provide estimators for the missing attributes in the current dataset and simplify the model (Section 3.2).

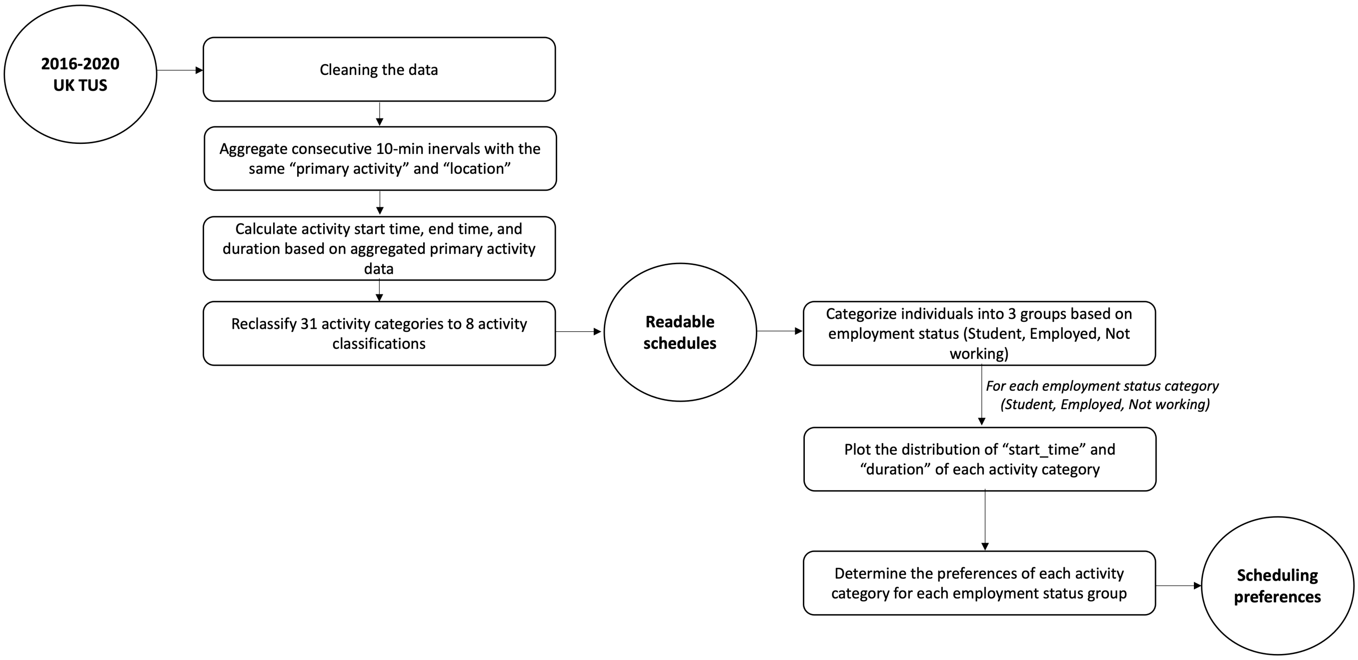
3.1 Data pre-process

The UK 2016-2020 TUS (Gershuny and Sullivan, 2021) has been used to showcase the scheduling model framework. 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 from 2202 individuals 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 of individuals and households, household equipment, device use, preferences and satisfaction, effects of lockdown, and diary information on activity, location, and accompaniment.

It is notable that the dataset report both primary and secondary (activity done simultaneously with the primary activity) activities in each 10 minute interval. In this study, we have only used the primary activities and not the secondary activities.

The data is first processed to obtain a readable schedule. Then, the scheduling preferences of different employment groups is derived from it. Figure 2 illustrates the steps to process the data. The processing steps which need further explanation are discussed in subsections 3.1.1 and 3.1.2.

Figure 2: Data pre-processing steps



3.1.1 Activity type reclassification

In the original dataset, we have 31 categories of activities. In order to enable reasonable model estimation, we have aggregated the initial activity categories in 2016-2020 UK TUS to 9 activity categories; work, study, home care, personal care, shopping, leisure, sleep, and trips. This classification has been done in accordance with Pawlak *et al.* (2021). Table 1 presents the mapping between the activity coding used in this research and the initial activity coding in 2016-2020 UK TUS data.

[1] 'Work, study break' activities are reclassified in either 'Work' or 'Study' activity category based on their preceding/following activity. Also, based on their duration, they are accounted as either ‘Leisure' (duration <=20 min) or ‘Work'/'Study' (duration>20 min)

[2] 'Walking,jogging' activities is categorized either under 'Trips' or 'Leisure' based on the location before/after them. If both the locations before and after 'Walking, jogging' activity are 'Home', it is labeled as 'Leisure', and otherwise as 'Trips'.

Table 1: Activity codes mapping between the 2016-2020 UK TUS and current study

Activity category in current research	Initial activity category in 2016-2020 UK TUS data	Initial activity code
Work	Paid work	117
	Work,study break[1]	125
Sleep	Sleeping	101
	Resting	102
Home care	Preparing food, cooking	105
	Cleaning, tidying housework	106
	Clothes washing, mending	107
	Maintenance daily	108
	Caring for own child	121
	Caring for other children	122
	Help, caring for cores adult	123
	Help, caring for non-coresidents	124
Personal care	Washing, dressing	103
	Eating, drinking	104
	Consuming services	109
	Going out to eat, drink	130
Study	Formal education	118
	Work,study break[1]	125
Leisure	Recreational courses	119
	Watching TV, video, DVD, music	127
	Reading including e-books	128
	Playing sports, exercise	129
	Playing computer games	132
	Time with friends, family	133
	Telephone, text, email, letters	134
	Cinema, theater, sport	135
	Hobbies	136
	Write-in other	137
	Dog walking	131
	Walking, jogging[2]	111
Organisational work	Church, temple, synagogue, prayer	110
	Voluntary work for organisation	120
Shopping	Shopping, bank including internet	126
Trips	Walking, jogging[2]	111
	Travel: cycle	112
	Travel by car	113
	Travel by bus, tram	114
	Travel train, tube	115
	Travel other	116

3.1.2 Employment status mapping between the TUS and the current study

In order to derive the scheduling preferences of individuals from the data, we have first classified individuals into three groups based on their employment status (student, employed, and not working). We have then determined the preferences of each category based on a statistical analysis on the data. Table 2 presents the current mapping.

Table 2: Employment status mapping between the 2016-2020 UK TUS and current study

Employment category in current research	Initial employment category in 2016-2020 UK TUS data
Employed	Self-employed with no employees Self-employed with 1-25 employees Employed Partner/director/owner company of 25+ employees Casual worker- not in permanent employment
Student	Student
Not working	Housewife/Homemaker Retired and living on state pension Retired and not living on state pension Unemployed or not working due to long-term sickness Full-time carer of other household member

3.2 Modeling assumptions

As all the required inputs to the scheduling model are not all available in the survey, we have made some realistic assumptions and heuristics to estimate the missing attributes including activities flexibility profiles, travel times, and scheduling preferences.

Activities 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. Activities in this category have high start and duration flexibility.
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 3 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).

Table 3: Flexibility profiles for activities in the UK TUS

Activity label	Start flexibility	Duration flexibility
Work	Early:MF, Late:NF	Short:NF Long:MF
Sleep	Early:F Late:MF	Short:MF Long:F
Home care	Early:MF Late:MF	Short:MF Long:F
Personal care	Early:F Late:F	Short:F Long:F
Study	Early:NF Late:NF	Short:NF Long:MF
Leisure	Early:F Late:F	Short:F Long:F
Organisational work	Early:MF Late:MF	Short:MF Long:MF

Travel time assumption: In the UK survey data, we only know the descriptive location of the activities; location is either recorded as 'Home', 'Work', or 'Other'. As we do not have the geographical coordinates of the activity locations, the travel times cannot be determined using the existing methods and tools. Therefore, as a preliminary assumption, we have assumed the following travel time matrix.

Table 4: Travel time matrix(hr)

Origin \ Destination	Home	Work	Other
Home	0	0.5	0.25
Work	0.5	0	0.25
Other	0.25	0.25	0

Activities start time and duration preference: In order to determine the activities start and duration preference of individuals in each of the three employment categories (student, employed, not working), we have plotted the distribution for each. We have then assumed that the mode of each distributions presents the preference.

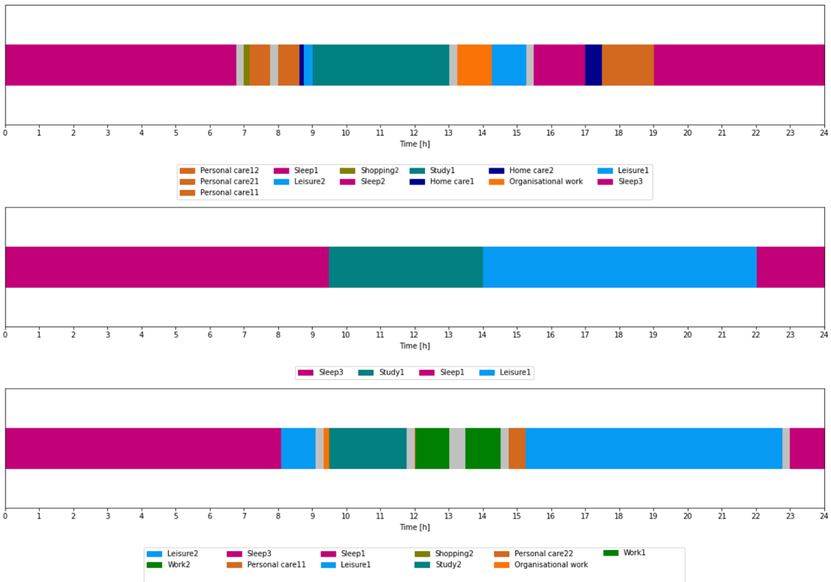
4 Results and discussion

The following analysis is performed to simulate likely schedules for a student during a weekday. Figure 3 presents three unique schedules from the model results for a student during a weekday. The presented model results are random draws from the feasible distributions of schedules generated from different draws of the error term. The grey bars between the activities show trips. In the simulated schedules, 'Work' activities ending in '1' correspond to activity location choice of 'Home', and the 'Work' activities ending in '2' correspond to location choice of 'Work'. 'Study', 'Personal care', 'Leisure', and 'Shopping' activities ending in '1' present the activity location choice as 'Home', and the same ones ending in '2' show that the activity location choice is 'Other'. You can see three sleeping activities in the simulated schedules: 'Sleep1' and 'Sleep3' represent overnight sleep, and 'Sleep2' presents naps during the day. The suffixes '1' and '2' right after 'Home care' and 'Personal care' show whether it is a morning or afternoon/evening home care or personal care, respectively.

Looking at the simulated schedules for a student during a weekday (Figure 3), 'Study' is the central activity, scheduled as or very close to the preference. We can observe that the deviations are mostly in the more flexible activities such as 'Leisure', 'Personal care', 'Home care', and 'Shopping'. This is because they are more flexible and have less penalty if deviated from their preferred time-slot. In the last simulated schedule, we can see a simulated schedule for a student who works part-time as well as studying. In this case, we can see that the utility of 'Work' activity has been valuable enough to shorten the 'Study' activity.

Simulating the schedule of individuals throughout the day and within the same framework; rather than modeling in- and out-of-home activities as separate phenomena (which is the case in the current activity-based models used by transport modelers) allows us to capture the trade-off between activities in- and out-of-home.

Figure 3: Model results for a student (weekday)



5 Conclusions and future work

In this paper, we have proposed a new viewpoint on activity scheduling of individuals and its possible applications. The main contribution of our research is modeling the in-home activities in addition to the out-of home activities within the same modeling framework. This study is building upon the scheduling approach developed by Pougala *et al.* (2021), which was originally utilized in activity-based transportation simulation, modeling only the out-of-home activities. Information on joint in- and out-of-home activity scheduling can serve for two primary purposes: First, the time-use pattern inside home can be later used by researchers in the domain of building energy modeling to predict energy demand at high temporal resolution. This can contribute to demand side management. 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, this scheduling approach is applicable to jointly model the time-use in home as well as the activities outside home.

There are further extensions that can be applied to the scheduling model. One major opportunity to extend the current scheduling approach is to investigate the household interaction effects and interpersonal dependencies which can affect the scheduling of in-home as well as out-of-home activities. The current framework, assumes activity scheduling at the level of isolated individuals. However, individuals do not plan their day in isolation from the household context. Different interactions and constraints exist for individuals scheduling their day as a member of a household. The intra-household interactions can be broadly considered as follows :

- car availability limitation
- resource constraints; for example two people cannot occupy the bathroom at the same time
- the effect of number of people/children in the household affecting the choice of individuals to stay at home or do activities out-of-home
- sharing household maintenance responsibilities by family members
- joint participation of household members in maintenance and leisure activities
- sharing common household vehicles
- facilitation of activity participation of household members with restricted mobility by undertaking pick-up and drop-off trips; such as dropping and picking children from school
- coordination of daily rhythms between couples; such as coordination of sleep and waking-up times between partners.

A better understanding of the within-household interactions can be used to simulate more complex and realistic schedules which can be used for setting more effective demand side management measures. So, in the next step, we extend the scheduling framework. We think of unselfish individuals, coordinating their time schedules to achieve the optimal schedule for the household, and we consider a utility function for the household. The framework treats the households as utility maximizers, maximizing the sum of utilities of completed activities in a time budget for the household. This framework would encompass: (1) the activity scheduling at the level of household; rather than at the level of isolated individuals, (2) capture interactions, and (3) capture resource constraints. The proposed framework is a general framework applicable to different household compositions and available resources. This will address the limitation of current models applicable to specific cases.

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