FRAMEWORK FOR GENERATING 7-DAY ACTIVITY SCHEDULES CONSIDERING HOUSEHOLD INTERACTIONS

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ABSTRACT

This paper introduces a novel framework for generating activity schedules in the context of households over a 7-day period. By combining an activity generation model based on the Multiple Discrete Continuous Extreme Value (MDCEV) approach with a constraint satisfaction optimization approach, the proposed framework addresses the limitations of existing studies that focus on single-day activities. The MDCEV model estimates utility parameters for different activities and income levels based on data from the German Mobility Panel, providing a foundation for understanding activity preferences. The schedule frame and fine-tuning models then generate realistic schedules, considering work hours, joint activities, and leisure time. Although the model is in its prototype phase, it already demonstrates promising results and can be integrated into agent-based travel demand models like mobiTopp and MATSim. Future work will involve further calibration and exploration of chore allocation within households, the impact of flexible work arrangements, and the influence of non-travel activities such as online shopping on activity patterns and travel behavior. Overall, this research contributes to a more holistic understanding of household interactions and provides valuable insights for travel demand modeling and urban planning.

Keywords: activity-based model, activity-schedules, MDCEV, household interactions, multi-day model

INTRODUCTION

Activity-based approaches have become state-of-the-art in travel demand modelling due to their behavioural realism. While there have been great advances in modelling techniques, most studies do not consider the household context, and almost all are limited to the generation of single-day activity schedules. Therefore, we propose an activity generation and scheduling approach for one week, considering the household context. This study provides a general overview over the proposed framework, and further details the model used to generate household-level activity time-use for the period of one week.

Activity-based approaches can be categorised into rule-based and econometric models. Rule-based models rely on hard-coded rules and heuristics, which make them easier to implement. However, this limits their behavioural realism and the ability to generalise model results. Econometric approaches mitigate these limitations by modelling individual decisions, not through rules and heuristics, but based on the principle of utility maximisation. Bowman and Ben-Akiva (*1*) presented the first disaggregate activity-based approach, which generates activity schedules by sequentially modelling individual decisions through (nested) logit models. Although the sequential model of decisions remains a popular approach in activity-based travel demand models, the method has some limitations. The sequence in which the analyst considers the decisions in the model claims that there is an order among the individual decisions. This possibly arbitrary order does not allow for consideration of trade-offs between all choices. This limitation has given rise to the development and application of the multiple discrete-continuous extreme value (MDCEV) model (*2, 3*). In this approach, individuals do not consider alternatives as perfect substitutes for each other but simultaneously as a combination of different activities and the time allocated to them, subject to a time budget constraint. While the first formulation of the model only allowed for modelling aggregated time allocation to each activity type, more recent studies show that the model can also consider activity episodes (*4*) and their order (*5*). Another approach to overcome some of the limitations of sequential models is to consider trade-offs between daily scheduling choices by formulating an optimization problem (*6, 7*). In this approach, the objective is to maximise the utility of an individual's schedule through a mixed-integer linear program. Although the presented approaches all improve state-of-the-art activity-based models, some limitations are worth noting. First, they only consider activities and their schedules for one day. However, past studies highlight the importance of considering multiple days for a more realistic simulation of travel behaviour within travel demand models (*8, 9*). Furthermore, all choices are considered on an individual level and most studies do not adequately consider the context of the household (*10*). While this is sensible for some activities like work or work-related activities, the household context influences who conducts certain activities, such as shopping or escorting activities. The interaction of intra-household activities has been analyzed frequently in the past (*11–17*), only few studies have included them in activity-scheduling frameworks.

Recently, studies have started to consider household interactions more holistically (*4, 5, 7*). However, the presented studies focus on a single day of activities and the proposed approaches cannot simply be transferred from the single-day to the 7-day context. Considering 7-day schedules and household context significantly in-creases the dimensions of the models, which will likely render the currently defined optimization problems too large to find a solution within a sensible timespan. Furthermore, we challenge that the underlying assumptions regarding the choice situations of scheduling activities still hold in the 7-day context. In utility theory, we assume that individuals know all possible alternatives within a choice set and choose the one that maximises their utility. Manser et al. (*6*) elaborate on the issue concerning this assumption regarding modelling activity schedules and present a method to generate a feasible choice set. Although the authors propose a sensible approach for single-day activity schedules, it is arguable whether activity schedules of one week actually result from individuals com-paring and choosing among a set of alternative schedules or rather from scheduling activities such that they meet a set of constraints. In this study we combine the idea of activity generation through an MDCEV model and the scheduling using an optimization approach and present the current state of our proposed prototype model. The rest of this paper is structured as follows. We will first provide an overview over the activity generation and scheduling framework. Subsequently, we describe the data used in our study and detail the model specification of the MDCEV model. We further elaborate on the two optimization problems formulated to construct activity schedules based on the input from the MDCEV model. We go on to present the estimation results and some preliminary findings on the scheduling process. Finally, we conclude our paper with future work and final remarks.

MATERIALS AND METHODS

This section, first provides an overview over the proposed framework. We subsequently provide a brief overview over the data used in this study, and finally specify the model.

Activity Generation Scheduling Framework

We propose an activity generation and scheduling approach for one week, considering the household context through a combination of the MDCEV model and a constraint satisfaction optimization approach. The framework for activity generation and scheduling is illustrated in figure . The input data can consist of either 7-day travel diary data or time-use data. Additionally, multi-day data generated through pattern sampling based on single-day data (as proposed by Zhang et al. (*18*)) is also possible.

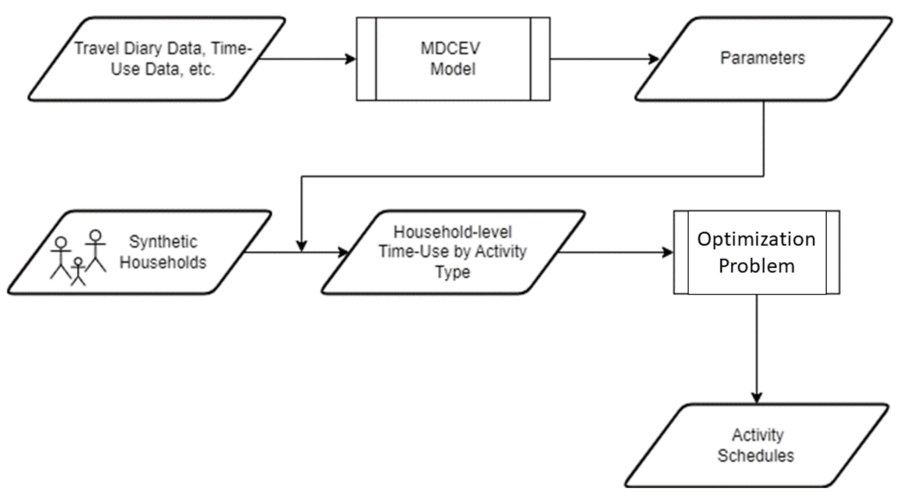

FIGURE 1 Overview over the proposed activity generation and scheduling framework

Based on this data, we estimate an MDCEV model. The estimated parameters are then applied to the synthetic population of the model region. At this stage, we define the model according to Bhat's (*2*) original formulation such that activities and the time allocated to them are predicted at an aggregate level.

Given the household-level activity types and times, the activity scheduler then considers each time slice of the activities and allocates it to a time slice within a household member's schedule. This discrete schedule frame is then used as input for a second optimization model in which the schedules are fine-tuned to generate minute-level activity schedules. Similar to Pougala et al. (*7*) and Manser et al.(*6*), we propose to define an optimization problem to generate these schedules. However, instead of the considering one day of travel, we formulate two optimization models to account for activities in one week.

Data

The data used in this study stems from the German Mobility Panel (MOP), a longitudinal survey that has been conducted annually since 1994. In the survey, participants report their trips in a 7-day travel diary in addition to providing personal and household information. For this study, we used data from 2017 to 2019, which includes data on 4.564 house-holds. As the data is collected using a travel diary and not a time-use diary, we had to pre-pare the data such that it reflects activity time-use. We set the start of each diary to mid-night of the first survey period and assigned the time until the first trip to "home". We repeated the same for the activity of the last trip of the week, setting the end of the diary to midnight on the last assigned survey day. We then determined the time-use for each activity per person and subsequently summarized the values at the household-level. At this point of development, we are considering six types of activities: home, work of household member 1, work of household member 2, shopping, leisure, and joint leisure activities. Further, we have included parameters to account for household information on income (high vs. low).

Household-Level Time-Use Estimation

The household-level time use is estimated using a MDCEV model approach as it was first presented by Chandra Bhat (Bhat, 2005). The model is specified such that home activities are treated as an outside good. Integrating an outside good ensures the positive consumption of that alternative; in this case the specification results in all individuals conducting a home activity. The problem is defined by:

$$max \sum_{k=1}^{K} \frac{\gamma}{\alpha} \psi_k((\frac{x_k}{\gamma_k}+1)^{\alpha}-1) \tag{1}$$

Subject to the budget constraint B

$$B=\sum_{k=1}^{K} x_k \tag{2}$$

where K is the number of considered activities, x_k is the amount of time spent on activity k. The budget of a household is the number of minutes per week (10.080) times the number of household members. The α and γ parameters determine the satiation. In our model, we specified α such that it does not vary over alternatives, while different γ parameters are determined for each alternative. The probability of an observed combination of activities including their duration is given by:

$$P(x_1^*, x_2^*, ..., x_M^*, 0, ..., 0) = \frac{1}{\sigma^{M-1}} (\prod_{m=1}^{M} f_m)(\sum_{m=1}^{M} \frac{p_m}{f_m})(\frac{\prod_{m=1}^{M} e^{\frac{V_i}{\sigma}}}{\sum_{k=1}^{K} e^{\frac{W_k}{\sigma}M}})(M-1)! \tag{3}$$

Scheduling

After determining the aggregated weekly time-use of a household, the model moves on to generate episodes and a schedule for each household member. This is done in two steps. In the first step, a schedule frame for each household member is created, which is the fine-tuned in the second step. In both steps, an optimization problem is solved considering all household member's schedules at the same time to allow for trade-offs between scheduling choices. Table 1 provides an overview of the sets, parameters, and variables included in the two optimization problems.

Both optimiziation problems are solved using IBM ILOG CPLEX Optimization Studio, version 20.1.0 (*19*) and called using the API for Python 3. We chose a commercial over an open-source software tool due to its fast run times (*20*), which is preferable during model development and calibration. However, once the model is fully implemented and integrated into the open-source travel demand simulation, we will move the model to an open-source solver.

TABLE 1 Sets, Parameters, Variables in Scheduling Optimization Problem

Sets	
$a \in \mathscr{A}$	Activity type
$a \in \mathscr{A}_w \subseteq \mathscr{A}$	Work activities
$a \in \mathscr{A}_s \subseteq \mathscr{A}$	Shopping activities
$a \in \mathscr{A}_h \subseteq \mathscr{A}$	In-home activities
$a \in \mathscr{A}_l \subseteq \mathscr{A}$	Leisure activities
$a \in \mathscr{A}_{jl} \subseteq \mathscr{A}_l \subseteq \mathscr{A}$	Joint leisure activities
$h \in \mathscr{H}$	Household members
$h \in \mathscr{H}_w \subseteq \mathscr{H}$	Employed household members
$d \in \mathscr{D}$	Day of the week
$d \in \mathscr{D}_w \subseteq \mathscr{D}$	Work days
$d \in \mathscr{D}_s \subseteq \mathscr{D}$	Days of the week where shops are open
$t \in \mathscr{T}$	Time of day
$t \in \mathscr{T}_s \subseteq \mathscr{T}$	Time of day when shops are open
$so_h \in \mathscr{T}_s \subseteq \mathscr{T}$	Shops opening time
$so_{cl} \in \mathscr{T}_s \subseteq \mathscr{T}$	Shops closing time
$e \in \mathscr{E}$	Episode index generated by schedule frame
Parameters	
ω	weighting parameters in schedule frame objective function
$tu_{a,hr} \in N_0$	household time-use by activity a at the hour-level
$tu_{a,min} \in N_0$	household time-use by activity a at the minute-level
$pws_h \in [1,24]$	preferred start of the workday of household member h
$mwd \in [1,24]$	maximum allowed daily work duration
$mdht \in [1,24]$	minimum time per day spent at home
Variables	
$x_{a,h,d,t} \in \{1,0\}$	Assignment of a to h on d at t
$ws_{h,d} \in [1,24]$	time of the first work activity of agent h on day d
$we_{h,d} \in [1,24]$	time of the last work activity of agent h on day d
$\delta ws_{h,d} \in [1,24]$	Absolute difference between pws_h and $ws_{h,d}$
$\delta wdur_h \in [1,24]$	Absolute difference of daily work duration of agent h between two days
$\lambda_{h,i,d,t} \in \{1,0\}$	Auxiliary variable; is 1 if household member h and household member i are at home on the same day d at the same time t
$\sigma_{h,d,t,u} \in \{1,0\}$	Auxiliary variable; is 1 if two consecutive work activities are the same
$\tau_{h,a,e}$	duration of episode e with activity purpose a, conducted by household member h
$\psi_{h,a,e}$	start time of episode e with activity purpose a, conducted by household member h

Schedule Frames

In the first scheduling step, schedule frames are created that represent schedules and episodes at a coarse temporal solution in time-steps of one hour. For this purpose, the time-use of a household estimated by applying the MDCEV-Model are first rounded to the full hour. For all activities that are non-home activities, the ceiling value is chosen to ensure that no activity is dropped. The time-use of home activities acts as a filler such that the time-use at the hour-level adds up to $24x7xh$, where h is the number of household members.

Although the travel times are estimated by the MDCEV-Model, we do not include them in this presentation of the prototype model. We will discuss how the travel times are included in a later paper, in which the travel simulation results and the underlying framework will be included. In this study, the travel times are added to the time-use at home.

This hourly discretized time-use of a household serves as input to the schedule frame optimization problem, which is defined as follows:

$$\max \omega_1 \sum_{h\in\mathscr{H}} \sum_{i\in\mathscr{H}} \sum_{d\in\mathscr{D}} \sum_{t\in\mathscr{T}} \lambda_{h,i,d,t} + \omega_2 \sum_{h\in\mathscr{H}} \sum_{d\in\mathscr{D}} \sum_{t\in\mathscr{T}} \sum_{u\in\mathscr{T}} \sigma_{h,d,t,u} - \omega_3 \delta wdur_h - \omega_4 \delta chores \tag{4}$$

subject to the following constraints:

$$\sum_{a\in\mathscr{A}} x_{a,h,d,t} = 1 \qquad \forall h \in \mathscr{H}, d \in \mathscr{D}, t \in \mathscr{T} \tag{5}$$

$$\sum_{h\in\mathscr{H}} \sum_{d\in\mathscr{D}} \sum_{t\in\mathscr{T}} x_{a,h,d,t} = tu_{a,hr} \qquad \forall a \in \mathscr{A} \tag{6}$$

$$\sum_{t=1}^{24} x_{a,h,d,t} \geq mdht \qquad a \in \mathscr{A}_h, \forall h \in \mathscr{H}, d \in \mathscr{D}, t \in \mathscr{T} \tag{7}$$

$$x_{a,h,d,t} = 0 \qquad \forall a \in \mathscr{A}_s, h \in \mathscr{H}, d \in \mathscr{D} \setminus \mathscr{D}_s, t \in \mathscr{T} \setminus \mathscr{T}_s \tag{8}$$

$$x_{a,h,d,t} = 0 \qquad \forall a \in \mathscr{A}_l, h \in \mathscr{H}, d \in \mathscr{D} \setminus \mathscr{D}_s, t \in \mathscr{T} \setminus \mathscr{T}_l \tag{9}$$

$$x_{a,h,d,t} = 0 \qquad \forall a = w_1, h = 2, d \in \mathscr{D}, \in \mathscr{T} \tag{10}$$

$$x_{a,h,d,t} = 0 \qquad \forall a = w_2, h = 1, d \in \mathscr{D}, \in \mathscr{T} \tag{11}$$

$$\sum_{t=1}^{24} x_{a,h,d,t} \leq mwd \qquad \forall a \in \mathscr{A}_w, h \in \mathscr{H}, d \in \mathscr{D}, t \in \mathscr{T} \tag{12}$$

$$x_{a,h,d,t} = 0 \qquad \forall a \in \mathscr{A}_w, h \in \mathscr{H}, d \in \mathscr{D} \setminus \mathscr{D}_w, t \in \mathscr{T} \setminus \mathscr{T}_w \tag{13}$$

$$\left| \sum_{t\in\mathscr{T}} x_{a,h,d,t} - \sum_{t\in\mathscr{T}} x_{a,h,e,t} \right| \leq \delta wdur_h \qquad \forall \{a \in \mathscr{A}_w, h \in \mathscr{H}, d, e \in \mathscr{D} : d \neq e\} \tag{14}$$

$$\sigma_{h,d,t,u} \leq x_{a,h,d,t} \tag{15}$$

$$\sigma_{h,d,t,u} \leq x_{a,h,d,u} \tag{16}$$

$$x_{a,h,d,t} + x_{a,h,d,u} - 1 \leq \sigma_{h,d,t,u} \qquad \forall \{a \in \mathscr{A}_w, h \in \mathscr{H}, d \in \mathscr{D}, t, u \in \mathscr{T} : u = t+1\} \tag{17}$$

$$|\sum_{d\in\mathscr{D}}\sum_{t\in\mathscr{T}} x_{a,h,d,t} - \sum_{d\in\mathscr{D}}\sum_{t\in\mathscr{T}} x_{a,i,d,t}| \leq \delta chores \quad \forall\{a\in\mathscr{A}_s, h,i\in\mathscr{H} : h\neq i\} \tag{18}$$

$$\lambda_{h,i,d,t} \leq x_{a,h,d,t} \tag{19}$$

$$\lambda_{h,i,d,t} \leq x_{a,i,d,t} \tag{20}$$

$$x_{a,h,d,t} + x_{a,i,d,t} - 1 \leq \lambda_{h,i,d,t} \quad \forall\{a\in\mathscr{A}_h, h,i\in\mathscr{H}, d\in\mathscr{D}, t\in\mathscr{T} : h\neq i\} \tag{21}$$

$$x_{a,h,d,t} = x_{a,i,d,t} \quad \forall\{a\in\mathscr{A}_j, h,i\in\mathscr{H}, d\in\mathscr{D}, t\in\mathscr{T} : h\neq i\} \tag{22}$$

The problem is formulated as a scalarizing multi-objective problem, in which the time that two household members spend at home together is maximized, while the number of work activity switches is to be minimized and the workduration between different days and the assignemnt of chores should be balanced. This objective is subject to a number of constraints. The first constraint (6) ensures that assignments are unique, i.e., that only one activity is assigned each time slot, and the second constraint ensures that the assignments add up to the aggregated time-use. Constraint (7) ensures that an agent has to spend a minimum number of hours per day at home, e.g., for maintenance activities. Constraints (8) and (9) consider that certain activities can only be conducted in given time frames. Shopping is constraint to (8) while leisure activities are constraint to a pre-determined preference (9). The latter is currently drawn from a distributions of the reported start and end times of first and respectively last leisure activities of the day. Constraint (12) limits the maximum number of day someone can work. This is currently set to 10 hours, but could be adapted to the type of job or other regulations, if the respective information is provided. Constraint (13) also pertains to work activities, in which work is limited to week days and provided work hours, which is currently set to 5 a.m. to 9 p.m. Again, these can be set individually for each agent. Constraint (14) ensures that the work duration is spread evenly throughout the week. Finally, constraints (15)-(17) are implemented to ensure that work is mostly conducted continuously and that the number of activity switches during the workday is limited.

Constraints (18) - (22) pertain to household interactions. In eq. (18), the split between the assigned chores is determined. Currently, the prototype model is formulated such that this split is balanced between household members. However, we will investigate if this assumption is correct. Literature for example shows that chores are more likely assigned to females compared to males, which we aim to integrate in the final model version (*21*). Constraints (19)-(21) pertain to the time that two household members spend at home together. This integrates the findings from (*22*) who show that household members value quality time together at home. Finally, the schedule frame is set up such that it already accounts for the fact that joint activities have to be conducted together (22).

Schedule Fine-Tuning

The result of the frame schedule is a list of episodes on and hour-level by activity purpose, including their order and the day on which they are conducted as well as the assignment to the household members. In the next step, the discrete schedules serve as input to the schedule fine-tuning problem, which turns them into minute-level activity schedules. The problem is defined as follows:

$$\min \quad \delta ws_1 + \delta ws_2 \tag{23}$$

subject to

$$\sum_h \sum_e \tau_{h,a,e} = tu_{a,min} \qquad \forall a \in A. \tag{24}$$

$$\psi_{h,a,e} = \sum_1^e \sum_a \tau_{h,a,e} \qquad \forall h \in \mathscr{H} \tag{25}$$

$$\psi_{h,a,e} = 0 \qquad \forall h \in \mathscr{H} \& e = 0. \tag{26}$$

$$\delta ws_h = \sum_e \left| \psi_{h,a,e} - pws_h \cdot 60 + day_e \cdot 1440 \right| \qquad \forall h \in \mathscr{H}_w, e \in \mathscr{E}_{fd}, a \in \mathscr{A}_w \tag{27}$$

$$\psi_{h,a,e} \geq pls_h \cdot 60 + day_e \cdot 1440 \qquad \forall h \in \mathscr{H}, a \in \mathscr{A}_l, e \in \mathscr{E} \tag{28}$$

$$\psi_{h,a,e} = \psi_{i,a,f} \tag{29}$$

$$\tau h, a, e = \tau i, a, f \qquad \forall h, i \in \mathscr{H}, a \in \mathscr{A}_j, e, f \in \mathscr{E}_a : h \neq i, e = f \tag{30}$$

$$\psi_{h,a,e} \geq sh_o \cdot 60 + day_e \cdot 1440 \tag{31}$$

$$\psi_{h,a,e} + \tau_{h,a,e} \geq sh_{cl} \cdot 60 + day_e \cdot 1440 \qquad \forall h \in \mathscr{H}, a \in \mathscr{A}_s, e \in \mathscr{E} \tag{32}$$

$$\psi_{h,a,e} + \tau_{h,a,e} \leq pht_h \cdot 60 + day_e \cdot 1440 \qquad \forall h \in \mathscr{H}, a \in \mathscr{A} \tag{33}$$

The objective function (eq. 23) of this problem is much simpler. The objective of the problem is to ensure stability between workdays throughout the week (*8*). Although the objective is simple, there are quite a few constraints surrounding the decision variables $\tau_{h,a,e}$, which refers to the exact duration in minutes of an episode e for activity purpose a assigned to agent h and $\psi_{h,a,e}$, the start time of these activities. The start times of each episodes are determined in minutes and refer to the start of the week, e.g., $\psi_{h,a,e} = 4993$ refers to the 4,993th minute of the week, which translates to Thursday, 11:13 p.m. The episodes are passed from the schedule frames in different ways. Indices are produced as a sorted sequence over all episodes, as a sorted sequence over episodes of the same activity purpose, or as a sorted sequence over one day and activity purpose. This allows us to make several different comparisons between two episodes. Similar to the schedule frame model, constraint (24) ensures that all episodes given their duration $\tau_{h,a,e}$ add up to the time-use of the household that was determined by the MDCEV model. In this case, this is the actual time-use at the minute-level. The two constraint (25) and (26) define the start time $\psi_{h,a,e}$ of an episode, based on its duration $\tau_{h,a,e}$. Essentially, all durations of previous episodes are added up and constraint (26) handles the case of an episode being the first in a schedule. The variable δws_h used in the objective function is defined in (27), by determining the absolute difference between the first work episode of a day and the preferred work start time. Similarly, the preferred start time for leisure activities is regarded in constraint (28). Constraints (29) and (30) ensures that joint activities are conducted at the same time (29) and have the same duration (30). Shopping is again constraint to shop opening hours, as defined in (31) and (32). Finally, each household member is assigned a preferred time by which they would like to be home (33). Similar to the work start time, this value is currently polled from the distribution of arrival times at home after the last out-of-home episode.

RESULTS AND DISCUSSION

In this section we provide an overview over the results of the proposed model. We first describe the results from the MDCEV model estimation and go on to present the results of the schedule frame and fine-tuning model parts. Table 2 provides the estimated parameters of the MDCEV model on household-level activity time use.

TABLE 2 MDCEV-Estimation results

activity	δ-coefficient	γ-coefficient
work hh-member 1		1163.34394
intercept	-5.923	
high Income	0.2137	
work hh-member 2		1074.92137
intercept	-7.546	
high Income	0.39811	
leisure		220.09584
intercept	-3.767	
high Income	0.021	
joint leisure		437.60339
intercept	-4.71023	
high Income	0.14193	
shopping	-2.806	24.43087
travel	3.293	0.05656

The results show that travelling has largest the δ parameter indicating that this is the most popular activity. This is not surprising as in our case, all activities (except home) are bound to travelling to a different location. On the other hand, considering the satiation parameter of travel, we can see that the least time is invested in travel. All other utility (δ) parameters are relatively similar. Compared to the other activities, shopping is rather popular. This reasonable, as almost all households conduct some shopping activity throughout the week.

Work from both household members have a relatively low utility, although both coefficients for higher income are positive. Despite the low utilities, the satiation parameters show that a lot of time of the weekly time budget is spent on work activities. Interestingly, both the δ- and γ-coefficients indicate that the second household member participates less often in paid work activities. Although we did not assume a head of household based on any measures, but used the IDs the respondents provided in the survey, there seems to be a survey effect on who identifies themselves as the primary bread winner and head of household.

Leisure activities are less popular than shopping activities, indicating that households conduct fewer leisure activities compared to shopping, however, the satiation parameter shows that a comparatively large amount of time is invested. Although the utility coefficient is lower for joint activities, the satiation parameter is larger, indicating that more time is invested into joint activities. It should be highlighted, that the model is based on household time-use based on the number of household members. Joint leisure is, therefore, considered twice meaning that although the satiation parameter is higher, given that both household members invest the same amount of time, i.e., when joint activities are conducted, axiomatically, both household members contribute to the time investment. There are few comparable studies that allow for a discussion of the model results in relation to other research. Although the studies on application of the MDCEV models continue to rise, few studies have regarded the household in time-use studies based on the MDCEV model, and most have focused on individual choices. Our model is most similar to the aggregated time-use model presented by Palma et al. (*4*). In this study, the authors also find that travelling is considered the most popular activity, whereas work and escorting activities are less popular.

Next we present results of the scheduling models. Figure 4 shows an output of the schedule frame models from a two-person household, in which both household members are employed fulltime. The figure shows that the work hours are evenly split across the five workdays. Joint activities are scheduled at the same time, while individual leisure activities are individually scheduled. Both household members are home during the night, showing reasonable scheduling results. Somewhat unrealistic is the switch back home after one hour of work on Thursday in the top schedule. Although this is controlled for by the activity switch constraint, the weights of that constraint used in the objective function are not yet fully calibrated.

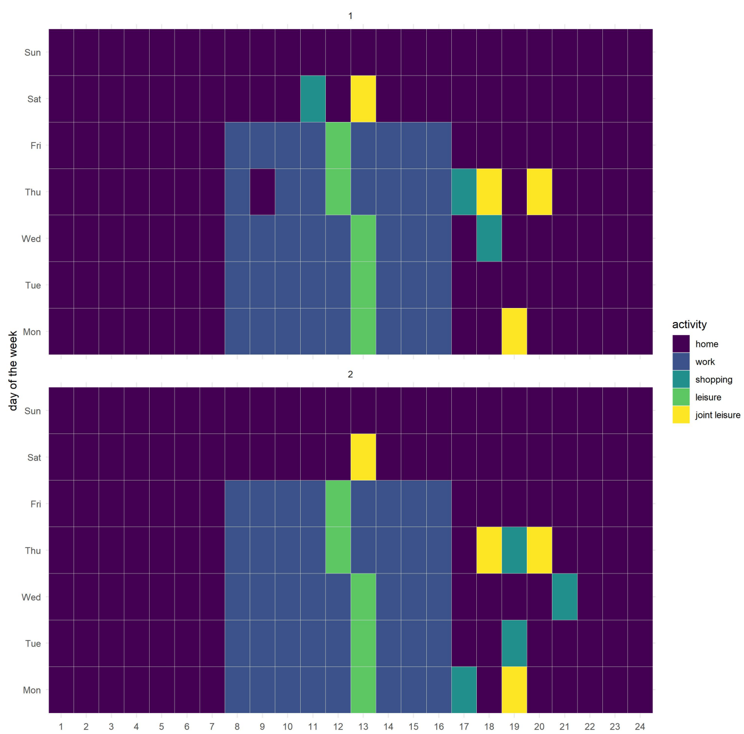

FIGURE 2 Output of the schedule frame model

Based on this schedule frame, the fine tuning model generates schedules for the two-household members at the minute-level. The output of that model for the same household as before is presented in Figure 4. We can see, that in the top schedule, the work start times are consistent throughout the week. This is not the case for the second schedule. The joint activities are held in place and are scheduled at the same time and have the same durations.

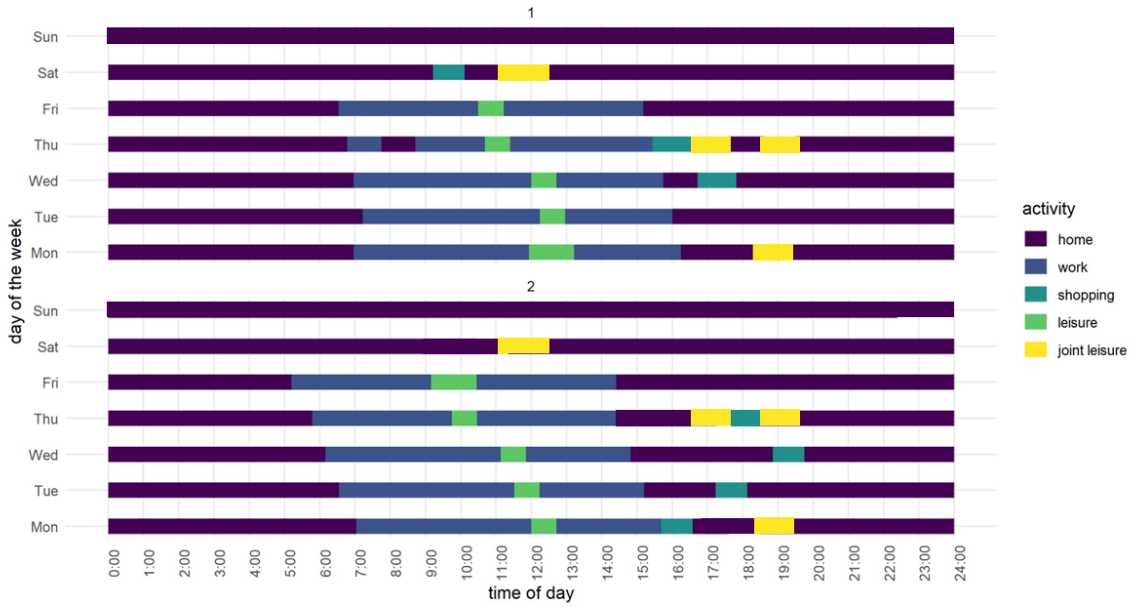

FIGURE 3 Output of the schedule fine tuning model

Looking at the start times of all generated schedules (Figure 4), we can see that, although the prototype is not fully calibrated, the start times are generally realistic. There is a large morning peak for work activities. Trips back home are consistent with afternoon peak hours. Joint leisure and leisure activities show similar distributions with slight peaks around lunch and in the afternoon. Shopping activities are scheduled relatively evenly throughout the day.

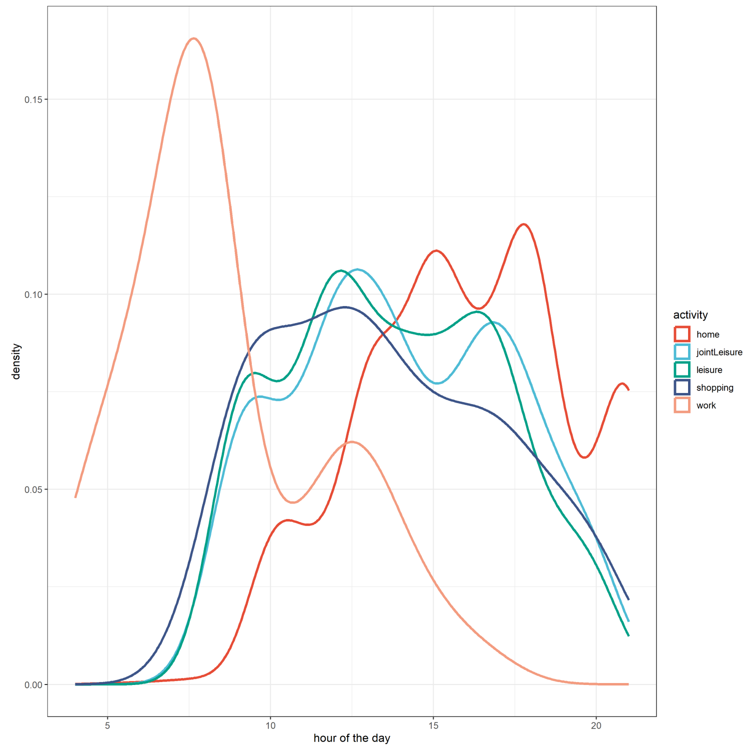

FIGURE 4 Distributions of episode start times

Although still in the prototype phase, the model already shows realistic results and is able to generate sensible schedules. Once calibrated and applied to a synthetic population, it will can serve as input to agent-based travel demand models. In a first step, the model is integrated into mobiTopp (*23*), as the framework already allows for the simulation of multiple days and up to a week. As mobiTopp can combined with MATSim simulations (*24*), the model will also be used for MATSim simulations.

Future work

Beyond calibration, there are multiple avenues that will be explored. Firstly, the allocation of chores: because the model accounts for time use at the household level for multiple days, it allows for the analysis of how household chores are distributed among its members. This pertains, e.g., to shopping activities and escorting children to childcare. Although the allocation of chores among household members has considerable effect on scheduling (*25*), the effect on travel has not gained as much attention (*26*). This will be a focal point of future work. It will be analyzed how different methods account for the allocation process, e.g. static proportions or sophisticated game theoretic approaches (*27, 28*).

Furthermore, the model allows for integration of flexible work arrangement and the consideration of their impact on time use and scheduling choices. Working from home considerably impacts activity patterns (*29*). Considering this effect in activity-scheduling models is especially important considering the increase in telecommuting since the Covid-19 pandemic (*10*).

Additionally, non-travel activities that influence activity patterns can be explored. As online shopping continues to rise, its impact on travel behavior will likely increase as well. As online shopping behavior and subsequent delivery traffic is already included in mobiTopp's last mile logistics extension logiTopp (*30*), the framework allows for easy integration of online shopping within the activity scheduling framework (provided appropriate data sources exist).

CONCLUSION

In conclusion, this paper presents a novel activity generation and scheduling framework that considers household interactions over a 7-day context. The proposed approach combines the use of an MDCEV model for activity generation with a constraint satisfaction optimization approach for scheduling. The results from the MDCEV model estimation show reasonable utility parameters for different activities and income levels. The schedule frame and fine-tuning models demonstrate the ability to generate sensible schedules for household members, considering work hours, joint activities, and leisure time. Although the model is still in the prototype phase and requires further calibration, it shows promising results and the potential to be integrated into agent-based travel demand models such as mobiTopp and MATSim.

Future work will focus on calibrating the model, exploring the allocation of chores among household members, considering the impact of flexible work arrangements, and investigating the influence of non-travel activities (e.g., online shopping) on activity patterns and travel behavior. Overall, this research contributes to a more holistic understanding of household interactions in the context of travel demand modeling and provides a foundation for further studies in this area.

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