An Optimization Framework For Daily Activity Schedules

Janody Pougala, Tim Hillel, and Michel Bierlaire

Ecole Polytechnique Fédérale de Lausanne (EPFL)

Abstract

Transport planners and operators have to face nowadays increasingly complex mobility behaviors. Traditional trip-based models become very limited in terms of behavioral accuracy when it comes to anticipating and accommodating these new, and hard-to-capture needs. The shift towards activity-based approaches is thus natural, as this alternative is better equipped to deal with individual-level granularity. The assumption behind these models is that all transport-related choices made by a person (e.g. number of trips, location and mode choice) are derived from the need to do activities, and their spatio-temporal sequence. We propose a modelling approach based on first principles: a traveler schedules their activities in order to maximize the total utility they can derive out of them, thus solving a mixed integer optimization problem. Our model allows to generate distributions of schedules for each individual, from which we can draw likely outcomes. Another contribution is the simultaneous inclusion of multiple choice dimensions (e.g. activity, location, mode choices…), allowing for more flexibility than current models that treat them sequentially. The model was tested using trip diary data from the Swiss Mobility and Transport Microcensus. The results show that we are able to generate realistic activity schedules for a wide range of individuals.

1 Introduction

The forecast of transportation demand is a key element to guarantee an efficient management of our increasingly urban environments. Trip-based models, which assume that the transport demand of a geographical zone can be estimated by aggregating the single trips made between different pairs of origins and destinations, are widely used in practice. While relatively easy to interpret, the simplifications induced by these models considerably limit their accuracy (Castiglione et al. 2014). Specifically, they do not consider the demand at the level of the individual, but rather an aggregated measure for a seemingly uniform population. Activity-based models (ABM) aim to provide a more realistic framework to the demand forecasting. Their fundamental principle is that travel is derived from the need to do activities (Axhausen & Gärling 1992, Bowman & Ben-Akiva 2001, Kitamura 1984). Trips depend on exogenous environmental features and on individual-specific attributes and preferences. Knowing the daily activity schedules of individuals thus allows to acquire a wider, behavior-oriented understanding of the demand, which in turn could help city planners and practitioners to improve their resulting decision-making processes.

This paper proposes an optimization framework to approach the activity-based problem, based on the assumption that individuals schedule their daily activity by maximizing the utility provided by their chosen schedule. The framework allows to produce a realistic distribution of schedules for a given individual, from which it is possible to draw likely outcomes.

Utility-based models have been a significant stream in ABM research. Econometrics models such as the sequential discrete choice framework proposed by Bowman & Ben-Akiva (2001), the discrete-continuous extreme value model developed by Bhat (2005), or the activity generation model by Nurul Habib & Miller (2009) apply the utility maximization theory to explain the scheduling process and the subsequent travelling demand. More practical approaches to the generation of realistic activity schedules have resulted in various simulation models: e.g. STARCHILD (Recker et al. 1986), SMASH (Ettema et al. 2000) CEMDAP (Bhat et al. 2004), PlanomatX (Feil 2010). Several of these models have been critiqued for their lack of behavioral realism, mainly due to a purely sequential approach (e.g. Bowman & Ben-Akiva (2001) that consider the decision making process as a series of tour-related chocies) lacking in flexibility to integrate dynamic dimensions such as household interactions. Models such as the SCHEDULER (Golledge et al. 1994) attempt to solve this issue, but remain difficult to generalize and calibrate.

Our framework attempts to solve these issues, by allowing a simultaneous optimization of multiple decision levels (e.g. activity type, sequencing, mode choice) and by introducing a layer of randomness through an error term, allowing to generate probabilities.

Section 2 of the paper introduces the model and its underlying theory. After a discussion on requirements to generalize and apply the model to real data in section 3, results from the Swiss Mobility and Transport Microcensus are presented in section 4.

2 Integrated framework

2.1 Definitions

We introduce the following definitions:

1. **Time:** we assume time to be discretized in t time blocks of equal length, with T the time horizon (e.g. $T = 24$h),

2. **Space:** space is discretized in a finite set of locations $\mathcal{L}$. Each location is associated to at least one activity.

3. **Activity:** an activity i is uniquely defined as an action taking place in a physical location l, having a start time x_i and a duration τ_i. The sequence of activities $\{i, i+1\}$ generates a trip from location l_i to l_{i+1}, that can be performed using mode m. An activity than can be performed at multiple locations, or reached with different modes is modelled as multiple unique activities. For each individual n, we consider four possible sets of activities:

   (a) *Feasible set $\mathcal{F}^n$:* all possible activities available to the individual within a given time frame that might be larger than the time budget. For instance, for a daily scheduling process, the feasible set includes all activities that could be performed during the week, month, etc.,

   (b) *Considered set $\mathcal{C}^n$:* all activities that they consider performing within their time budget. For example, given a list of activities to be performed in a week, the considered sets includes activities that the individual plans to do in a given day. We let $\mathcal{C}^n \subseteq \mathcal{F}^n$,

   (c) *Scheduled set $\mathcal{S}^n$:* all activities scheduled for a given day, based on the set (or agenda) they had previously considered. We let $\mathcal{S}^n \subseteq \mathcal{C}^n$,

   (d) *Realized set $\mathcal{R}^n$:* all activities actually performed by the individual within their time budget. Given that the realized set is built from the scheduled set through external operations such as deletion, addition or substitution or activities, $\mathcal{S}^n$ and $\mathcal{C}^n$ could be distinct.

   Only the considered and scheduled set are in the scope of our research.

2.2 First principles

We assume that the scheduling behaviour of an individual n can be explained by the following first principles, based on the early works of Becker (1965) and Recker & Root (1981):

1. They have a time budget which constrains their activity schedules. Considering both in and out of home activities, the total duration of the schedule must be equal to the available budget.

2. Each considered activity i is associated with a utility U_{in}. This utility translates the satisfaction derived by the individual by performing the activity. We assume this utility to be time-dependent.

3. The scheduling process itself is assumed to be driven by the desire to maximise the total satisfaction, or utility, provided by the activities subject to the given time budget constraint.

In addition, an important assumption on the behavior of n is that they are time-sensitive, meaning that they have measurable preferences for the timing (start, end or duration) for each activity i. For instance, they might prefer going to the gym before going to work, or having at least one hour available if they eat at a restaurant. We assume that all schedule deviations from these preferences (i.e. differences between what can be scheduled given the constraints and what they would rather do) decrease the utility of performing the activity. Of course, this negative influence depends on the individuals and their own flexibility to change, which can vary from one activity to the other.

2.3 Utility function of activities

The central element of our framework is the utility U_{in} of performing activity i by the individual n. As expressed in Equation 1, the utility function is composed of five main components:

$$U_{in} \;=\; U_{\text{const}_{in}} \;+\; U_{\text{timing}_{in}} \;+\; U_{\text{duration}_{in}} \;+\; U_{\text{tt}_{in}} \;+\; \xi_{in} \tag{1}$$

- A constant utility of activity participation $U_{\text{const}_{in}}$. Assuming this constant to be null for all in-home activities, it represents the preference of performing the activity rather than staying at home, all other things being equal. Thus, activity i being selected in the schedule requires this term to be positive.

- Two terms $U_{\text{timing}_{in}}, U_{\text{duration}_{in}}$ capturing the (a priori negative) impact of schedule deviations on the total utility. Contrasting with Feil (2010), that only considers the disutility of being late to an activity, these terms express deviations in terms of both start time (early/late) and duration (too long/too short) respectively. They penalize divergences from the preferred schedule, to an intensity depending on the indivual's flexibility.

- A term $U_{\text{tt}_{in}}$ representing the utility of travelling to the location of the activity.

- A random term ξ_{in}.

Utility of schedule deviations

The utility of schedule deviations is based on the work of Small (1982). Considering the schedule preferences x^*_{in} (preferred start time) and τ^*_{in} (preferred duration) of person n for activity i, and x_{in}, τ_{in} the actual scheduled start time and duration, we define a schedule deviation as the difference between the preferred and the actual values. The possible deviations are an earliness or lateness in start time, or a shortened or prolonged duration, which are penalized respectively by factors $\theta_{ek}, \theta_{lk}, \theta_{dsk}, \theta_{dlk}$. These penalties do not depend on the activity itself, but rather on the flexibility of the individual for this activity, that we denote k. k can indicate three possible behaviors :

1. Flexible: deviations from preferences for activity i are permitted, thus are less or not penalized.
2. Moderately flexible: deviations from preferences are permitted, but are more penalized than in the flexible case.
3. Not flexible: deviations from preferences are not permitted, and are consequently highly penalized.

The values of the penalties associated to each flexibility profile are considered equal across individuals sharing the same category. The model can thus account for priorities between different activities, which is analogous to the traditional classification of activities encountered in the literature (e.g. mandatory, maintenance and discretionary, and similar variations) (Castiglione et al. 2014).

The relation between the different penalties should be defined. Intuitively, one can postulate that individuals do not penalize in the same way arriving early or late to the same activity, regardless of their flexibility. In terms of start times, this observation is confirmed by studies on departure time preferences (Arnott et al. 1987, Small 1982).

Fewer studies exist on the deviation from the optimal duration of an activity (which is in most cases the individual's preferred duration, but could be constrained by other factors e.g. the required daily working hours), however, several authors have identified possible *frustration* and *satiation* effects. (Ettema et al. 2007)

Equation 2 defines the impact on the utility of a deviation in regards to start time. When the activity is scheduled earlier than what is preferred (i.e. $x^*_{in} - x_{in} > 0$), the deviation is penalized through the term $U_{\text{early}_{in}}$, while $U_{\text{late}_{in}} = 0$. On the other hand, if the activity is scheduled later than preferred (i.e. $x^*_{in} - x_{in} < 0$), the deviation is penalized through $U_{\text{late}_{in}}$, while $U_{\text{early}_{in}} = 0$. If the scheduled start time is what the individual prefers (i.e. $x^*_{in} - x_{in} = 0$), the utilty is not penalized. The same logic is applied to the scheduled duration, as defined by equation 3.

$$\begin{aligned} U_{\text{timing}_{in}} &= U_{\text{early}_{in}} + U_{\text{late}_{in}} \\ &= \theta_{ek} \max\left(0;\ x^*_{in} - x_{in}\right) + \theta_{lk} \max\left(0;\ x_{in} - x^*_{in}\right) \end{aligned} \tag{2}$$

$$\begin{aligned} U_{\text{duration}_{in}} &= U_{\text{short}_{in}} + U_{\text{long}_{in}} \\ &= \theta_{dsk} \max\left(0;\ \tau^*_{in} - \tau_{in}\right) + \theta_{dlk} \max\left(0;\ \tau_{in} - \tau^*_{in}\right) \end{aligned} \tag{3}$$

Utility of travel

We consider the utility generated by travelling as a linear function of the travel time. As defined in §2.1, each activity i is defined by a unique location l_i, and can be reached from the location of the previous activity l_{i-1} by travelling with mode m_i. We assume that the impact of travelling on the utilty of the activity is negative, meaning that an activity with a longer travel component will be regarded less favourably than an activity requiring a shorter travel time. We name θ_{ti} the penalty associated with travelling, and we consider it equal across individuals.

$$U_{\text{tt}_{in}} = \theta_{ti} tt\left(l_{i-1}, l_i, m_i\right) \tag{4}$$

Random term

We include a random error term ξ_{in}, drawn from a normal distribution $\mathcal{N}\left(0, \sigma^2\right)$ (Eq. 5), with variance σ^2 to be estimated. A unique error term is drawn for each activity.

$$\xi_{in} \;=\; \sigma\epsilon_{in} \tag{5}$$

with $\epsilon_{in} \sim \mathcal{N}\left(0, 1\right)$

Total utility function

Replacing (2), (3), (4) and (5) into (1) yields the total, time-dependent utility function for activity i performed by individual n:

$$\begin{aligned} U_{in} \;=\; c_{in} \;+\; \theta_{ek} \max\left(0;\; x^*_{in} - x_{in}\right) \;+\; \theta_{lk} \max\left(0;\; x_{in} - x^*_{in}\right) \;+\; \theta_{dsk} \max\left(0;\; \tau^*_{in} - \tau_{in}\right) \\ +\; \theta_{dlk} \max\left(0;\; \tau_{in} - \tau^*_{in}\right) \;+\; \theta_{ti} tt\left(l_{i-1}, l_i, m_i\right) \;+\; \sigma\epsilon_{in} \end{aligned} \tag{6}$$

2.4 Mixed integer optimization problem

A person n with a set of considered activities A and a time budget T schedules all activities $a \in \mathcal{C}^n$ by solving a mixed integer optimization problem, where the total utility of all scheduled activitites is maximized.

$$\Omega = \max \sum_i \omega_{i_n} U_{i_n} \tag{7}$$

The decision variables of the problem are the following:

- ω_{i_n}: a binary variable equal to 1 if activity i is scheduled and 0 otherwise,
- z_{ij_n}: a binary variable equal to 1 if activity i follows activity j in the schedule and 0 otherwise,
- x_{i_n}, τ_{i_n}: positive continuous variables representing respectively the start time and the duration of activity i.

The problem is subject to a set of constraints:

$$
\begin{aligned}
\sum_i \sum_j (\tau_{i_n} + z_{ij_n} t_{ij_n}) \;&=\; T && && (8)\\
\omega_{\text{dawn}_n} \;=\; \omega_{\text{dusk}_n} \;&=\; 1 && && (9)\\
\omega_{i_n} \;&\leq\; \tau_{i_n} && \forall i \in \mathcal{C}^n && (10)\\
\tau_{i_n} \;&\leq\; \omega_{i_n} T && \forall i \in \mathcal{C}^n && (11)\\
z_{ij_n} + z_{ji_n} \;&\leq 1 && \forall i, j \in \mathcal{C}^n, j \neq i && (12)\\
z_{ii_n} \;&=\; 0 && \forall i \in \mathcal{C}^n && (13)\\
z_{i,\text{dawn}_n} = z_{\text{dusk},j_n} \;&=\; 0 && \forall i, j \in \mathcal{C}^n && (14)\\
\sum_{i, i\neq j} z_{ij_n} &= \omega_{j_n} && \forall j \in \mathcal{C}^n, j \neq \text{dawn} && (15)\\
\sum_{j, j\neq i} z_{ij_n} &= \omega_{i_n} && \forall i \in \mathcal{C}^n, i \neq \text{dusk} && (16)\\
(z_{ij_n} - 1)\, T \;\leq\; x_{in} + \tau_{i_n} + z_{ij_n} t_{ij_n} - x_{jn} \;&\leq\; (1 - z_{ij_n})\, T && \forall i, j \in \mathcal{C}^n && (17)\\
\sum_i \omega_i &\leq 1 && \forall i \in G && (18)\\
x_{i_n} &\geq \gamma_i^- && \forall i \in \mathcal{C}^n && (19)\\
x_{i_n} + \tau_{i_n} &\leq \gamma_i^+ && \forall i \in \mathcal{C}^n && (20)
\end{aligned}
$$

(8) constrains the total time assigned to the activities in the schedule (duration and travel time) to be equal to the time budget. (9) ensures that each schedule begins and end at home (*dawn* and *dusk* are respectively the first and last in-home activity of the day). (10) and (11) enforce consistency with the activity durations, by requiring, respectively, the activity not to take place if its duration is 0, and vice-versa. (12)-(17) constrain the sequence of the activities: (12) ensures that two activities can only follow each other once, (13) that an activity cannot follow itself, and (14), (15), (16) that each activity but the first has only one predecessor, and each but the last only one successor. (17) enforces time consistency between two consecutive activities. (18) ensures that only one activity within a group of duplicates (see 2.1) is selected. Finally, (19) and (20) are time windows constraints.

The outcome of the model is a feasible schedule S including activities from considered set $\mathcal{C}^n$, and complying with the constraints. As the utility functions of all activities depend on the error term, we expect different draws of ξ_{i_n} to generate different solutions.

3 Operational model

The model relies on a number of assumptions, and the required insights might not always be available in traditional data sources such as travel diaries. The challenge is thus to provide heuristics to obtain estimators for the missing attributes. Specifically, information such as the activities considered by the individual (as opposed to those they recorded in the travel diary), their preferences in terms of start time, duration or frequency of the activity, or their flexibility are difficult to derive from straightforward, factual surveys.

The main requirements to apply the model are, for an individual *n* and each of their considered activities: the desired start time and duration, the flexibility of the individual with regards to each activity and the subsequent penalty values, the travel time matrix for all pairs of considered locations, and all considered modes, and finally, the variance of the error term.

Table 1 summarizes the requirements in terms of data and two possible solutions to overcome the lack of information. The *heuristic* column describes methods that have been applied in the scope of this paper, with results described in §4.

Table 1: Data requirements for operational model

Requirements	Rigorous solution	Heuristic
Desired start times and durations	Habit analysis and identification of typical timings in multidays diaries	Out-of-sample distributions, with geographical sampling
Flexibility	Habit analysis in multidays diaires — flexibility would be the timing variability	Assign a flexibility profile to each activity based on literature classification
Penalty values	Calibrated on data — n-dependent	From literature, homogeneous across all population
Constant utility of activities	Calibrated on data	Captured by error term
Feasible time windows	Data collection	Minima and maxima values in out-of-sample distributions of start and end times for each activity, across the population
Travel time matrix	Build a set of considered locations within defined radius of home and work location (e.g. using geographical sampling), then use Google Maps distance matrix API	Use Google API between locations recorded by individual n in diary
Variance of error term	Calibrate from data	Trial and error, minimization of distance with optimal schedule

4 Empirical investigation

The model was applied using the Swiss Mobility and Transport microcensus (MTMC), a Swiss nationwide survey gathering insights on the mobility behaviours of local residents (OFS 2015). Each respondent provides their socio-economic characteristics (e.g. age, gender, income) and those of the other members of their household, and information on their daily mobility habits. A selected sample provided detailed records of their trips during a reference period (1 day). The 2015 edition of the MTMC contains 57'090 individuals, and 43'630 trip diaries. We tested the model on Lausanne residents only, reducing the number of diaries to 2'227.

From the 13 trip purposes (and an additional 18 *leisure* subcategories) available in the travel diaries, we have only kept 9: home, work, education, shopping, errands and use of services, business trips, leisure and escort. The start, end and durations of each activity were derived from the timings of the recorded trips. The latitude and longitude values were provided for each visited locations, and we used these measures to produce a travel time matrix using the Google Directions API for the car mode[1].

[1]We ignored the mode choice in the scope of this paper.

A major limitation of this dataset is the lack of qualitative information, such as the preferences of the individual in terms of start times and durations, their flexibility or simply whether the activities they have recorded for the day were freely chosen or constrained in any way. We have used the heuristic methods described in §3 to circumvent this issue:

- The desired start times and durations were assumed equal to timings recorded by the invidual.
- The feasible time windows were obtained using the average values for start and end times for each activity in an out-of-sample distribution, obtained using 30% of the observations in the Lausanne sample.
- We assumed that the individuals had visited all locations of their considered set. This implies that there can be no duplicates of activities and therefore constraint (18) does not apply.
- A category and a flexibility profile were assigned to each category, uniformly across all population (Table 2). Deviation penalties were defined based on this classification (Table 3[2]).

Table 2: Categories and flexibility profiles for activities in the MTMC
The following acronyms are used: F=flexible, MF=moderately flexible, NF=not flexible

Activity	Category	Flexibility profile	
Work		*Start*	*Duration*
Education	Mandatory	Early: NF	Short: NF
Business trip		Late: MF	Long: NF
Errands, use of services	Maintenance	Early: MF	Short: MF
Escort		Late: MF	Long: F
Home[3]			
Shopping	Discretionary	Early: F	Late: MF
Leisure		Short: F	Long: F

4.1 Results

We present two examples from the MTMC, identified as Person A and B. The set of considered activities for Person 1 contains two education activities (preferred in the morning, and in the afternoon), with a return at home during lunchtime. A leisure activity is also considered, to start at the end of the last education period, followed by a return home.

Figure 1 shows three unique outputs produced by the model, for two different draws of ξ. The first option (Fig. 1a) shows a sequence in which both *education* instances are scheduled, including the return home at noon. In the second option (Fig. 1b), the value of ξ makes the contribution of the *leisure* activity to the utility valuable enough to include it in the daily schedule, consistent with the individual's preferred timing. The third solution (Fig. 1c) also includes the leisure activity, however the proposed timing is significantly far from the preferences.

[2]The penalty values were arbitrarily assigned, using results from (Small 1982)
[3]Not including mandatory home stays *dawn* and *dusk*

Table 3: Penalty values by flexibility, in units of utility

Deviation	Flexibility	Penalty θ
Early start	Flexible (F)	0
	Moderately flexible (MF)	-0.61
	Not flexible (NF)	-2.4
Late start	F	0
	MF	-2.4
	NF	-9.6
Short duration	F	-0.61
	MF	-2.4
	NF	-9.6
Long duration	F	-0.61
	MF	-2.4
	NF	-9.6

Unsurprisingly, the changes in solution affect mainly the discretionary activity, for which deviations are far less penalized than its mandatory counterparts. The same observation can be made for Person B (Fig. 2), who had considered both a mandatory (*education*) and discretionary (*shopping*) activities. Fig. 2a and 2b both include shopping, but the scheduled timings are slightly different: the first solution (Fig. 2a) schedules the activity at 16h20, for a duration of 2.5 hours, whereas the other (Fig. 2b) proposes a start time at 16h30 for a duration of 2 hours. In the third solution (Fig. 2c), the shopping activity does not appear in the schedule, indicating that staying at home has a higher overall utility.

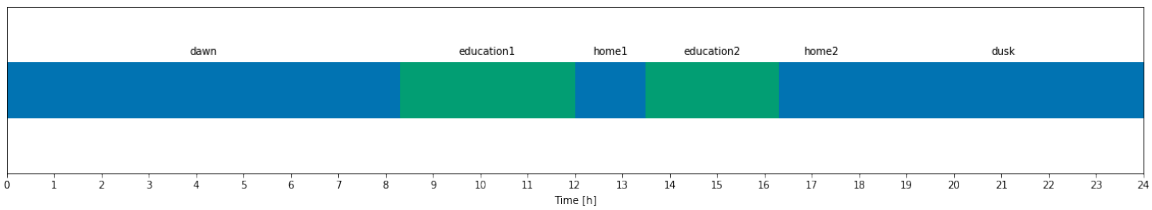
4.2 Sensitivity analysis

In order to characterize the stability of our model, we perform an entropy-based sensitivity analysis. We are especially interested in the influence of the variance σ^2 of the error term ξ_{in} (for activity i and person n), as well as the values of deviations penalties θ on the overall performance. Given a set of deviation penalties $\theta_m = \{\theta_e, \theta_l, \theta_{ds}, \theta_{dl}\}_m$ and a draw ξ^r_{in} from the distribution of error terms, the optimization problem (7) results in a unique solution S_{mr} (defined as a schedule, i.e. a sequence of activities with optimized start times and durations) with utility U_{mr}. For R draws, we therefore obtain a distribution of solutions and utilities, each solution S_{mr} being associated to a probability p_r, conditional to the drawn error term (and the chosen variance of its distribution). We can thus compute the entropy of the problem:

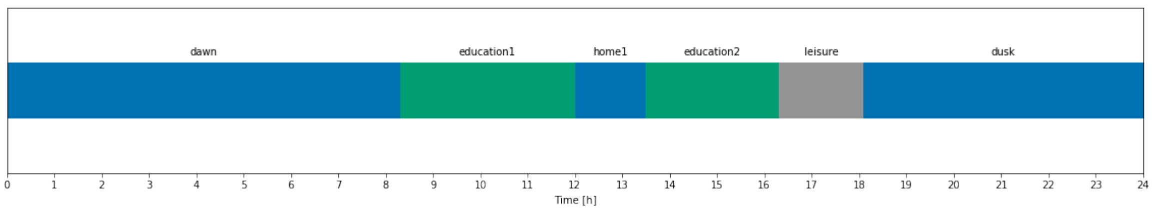
$$H_\sigma = -\sum_{r=1}^{R} p_r \ln(p_r) \tag{21}$$

Figure 3 shows the influence of the variance and penalty profiles[4] on the entropy for 1 person. The entropy of the solutions seems to increase with the variance, thus decreasing the determinism of the problem. Interestingly, we notice the presence of an inflection point (around $\sigma^2 = 7$), after which the entropy increases at a significantly

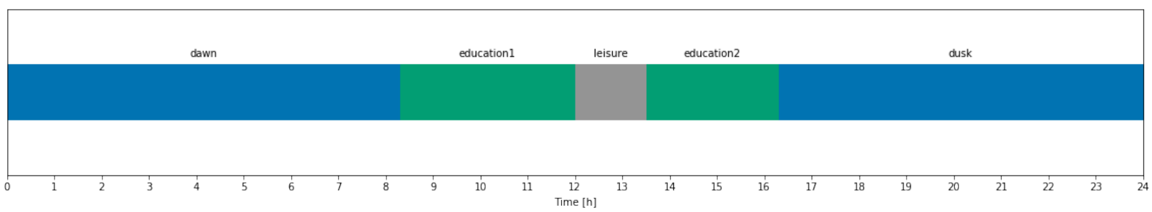
[4] Obtained by increasing the magnitude of the values presented in Table 3



(a) Solution 1

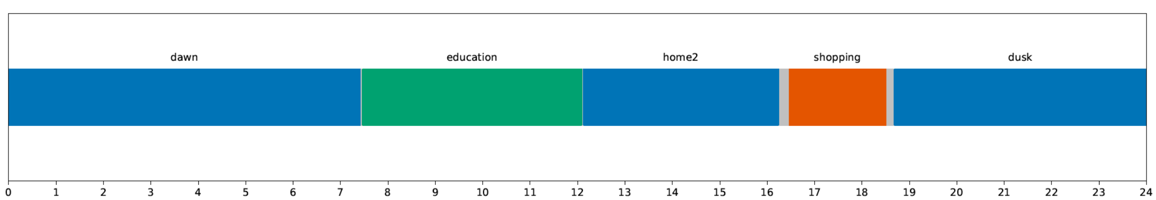


(b) Solution 2

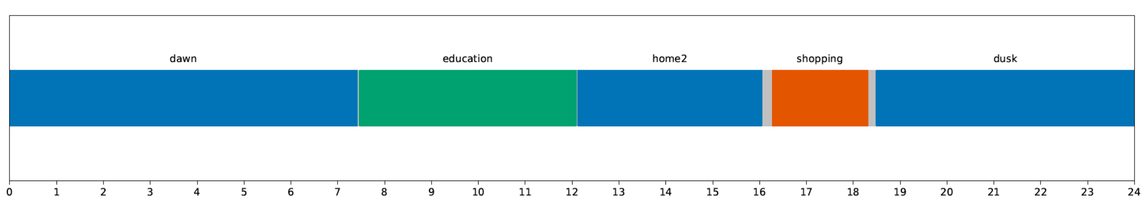


(c) Solution 3

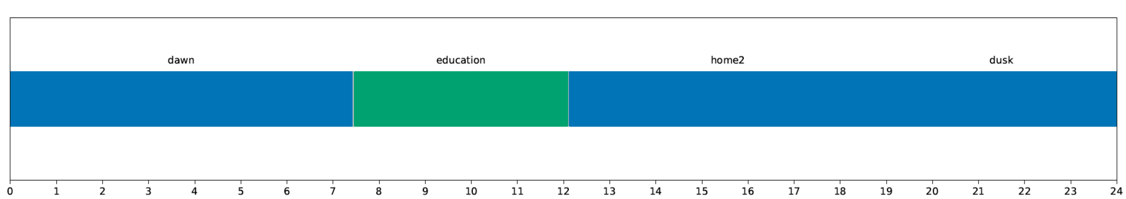
Figure 1: Person A



(a) Solution 1



(b) Solution 2



(c) Solution 3

Figure 2: Person B

smaller rate. On the other hand, different penalty profiles do not seem to have a strong effect on the overall entropy, as compared to a change in variance.

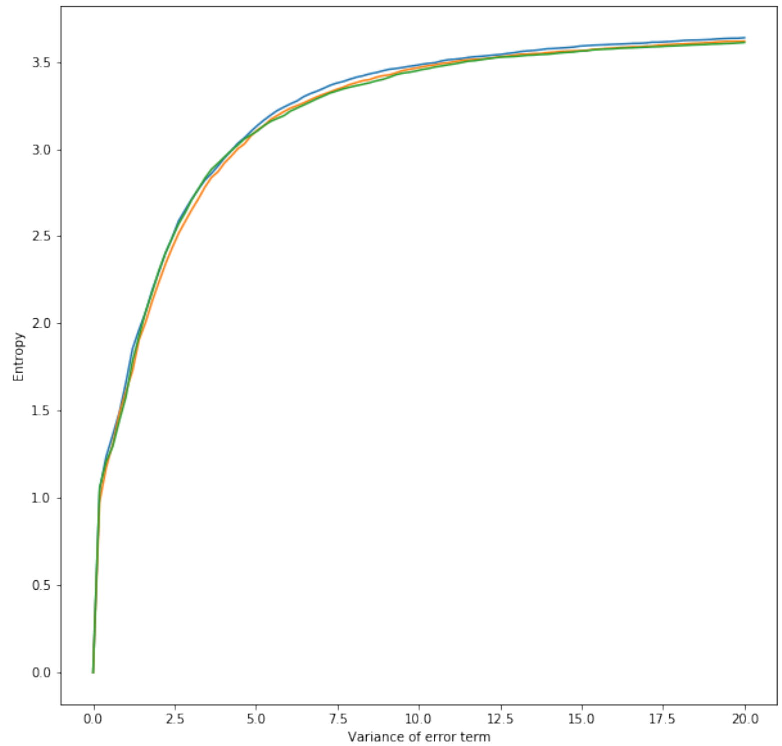
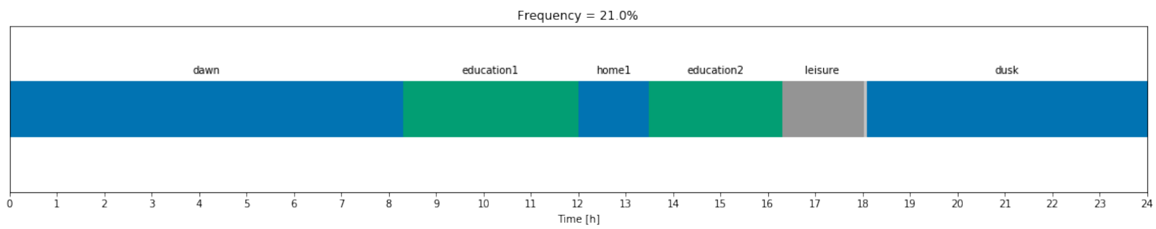


Figure 3: Influence of the variance of the error term and the penalty profiles on the final entropy). The curves correspond to 3 different penalty profiles.

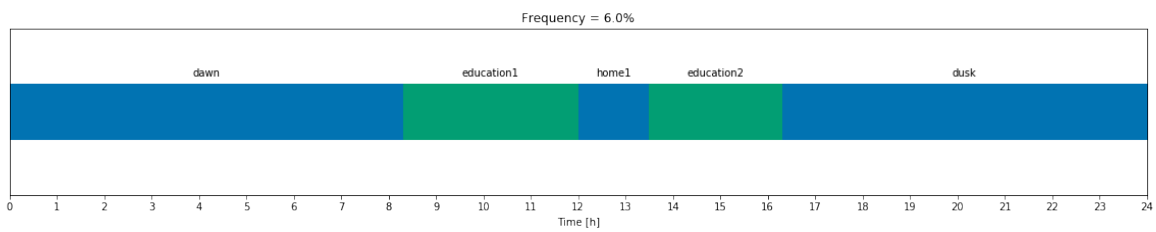
Figures 4a-4c show the most frequent schedules generated for the first individual, with variances $\sigma^2 = 0.5, 7.5$ and 20 respectively. As shown by the analysis of the entropy, an increasing variance indicates an increasing entropy, and thus a greater variety of solutions. For very small variances ($\sigma^2 = 0.5$), the problem is the most deterministic, with one schedule being particularly represented in the set of solutions (generated 21 times over 100 iterations) compared to the higher variances, where the frequency of a particular solution does not exceed 6%. One can observe that for the the two extreme variances ($\sigma^2 = 0.5$ and $\sigma^2 = 20$), the most frequently generated solution is, while valid in a mathematical sense, significantly far from the preferences. In the first case, there is a discrepancy between the end time of the leisure activity and the beginning of the *dusk* home activity. This is due to the fact that this solution replicates exactly the preferred sequence declared in the travel diary, which is not always continuous. In the second case, the variance is high enough to overshadow any declared priority between activities. These results highlight the importance of the choice error term in the generation of stable and realistic solutions.

4.3 Conclusion and future work

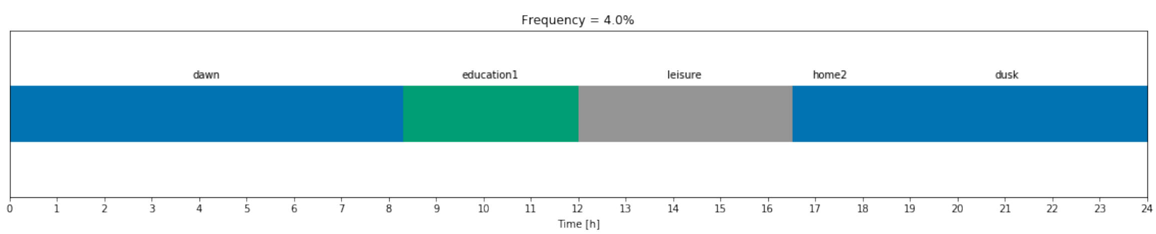
We proposed a preliminary definition of an optimization framework to solve the activity-based problem, based on the theory of utility maximization and first principles. The main contribution of our research is the generation of distribution of feasible activity schedules from random draws of the error terms, from which we can then draw a likely schedule for each individual. Future iterations of the work will include the development of a rigorous methodology to estimate the parameters of the utility function. Furthermore, the framework can be expanded with a Metropolis-Hastings algorithm to generalize the simulation process.



(a) $\sigma^2 = 0.5$



(b) $\sigma^2 = 7.5$



(c) $\sigma^2 = 20$

Figure 4: Most frequent schedules generated out of 100 iterations for values of σ^2

References

Arnott, R., De Palma, A. & Lindsey, R. (1987), *Schedule delay and departure time decisions with heterogeneous commuters*, University of Alberta, Department of Economics.

Axhausen, K. W. & Gärling, T. (1992), 'Activity-based approaches to travel analysis: Conceptual frameworks, models, and research problems: Foreign summaries', *Transport Reviews* .

Becker, G. S. (1965), 'A Theory of the Allocation of Time', *The Economic Journal* .

Bhat, C. R. (2005), 'A multiple discrete-continuous extreme value model: Formulation and application to discretionary time-use decisions', *Transportation Research Part B: Methodological* .

Bhat, C. R., Guo, J. Y., Srinivasan, S. & Sivakumar, A. (2004), 'Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns', *Transportation Research Record: Journal of the Transportation Research Board* **1894**(1), 57–66.

Bowman, J. & Ben-Akiva, M. (2001), 'Activity-based disaggregate travel demand model system with activity schedules', *Transportation Research Part A: Policy and Practice* **35**(1), 1–28.

Castiglione, J., Bradley, M. & Gliebe, J. (2014), *Activity-Based Travel Demand Models: A Primer*, Transportation Research Board, Washington, D.C.

Ettema, D., Bastin, F., Polak, J. & Ashiru, O. (2007), 'Modelling the joint choice of activity timing and duration', *Transportation Research Part A: Policy and Practice* .

Ettema, D., Borgers, A. & Timmermans, H. (2000), 'A simulation model of activity scheduling heuristics: An empirical test', *Geographical and Environmental Modelling* **4**(2), 175–187.

Feil, M. (2010), Choosing the Daily Schedule: Expanding Activity-Based Travel Demand Modeling, PhD thesis, ETH Zürich.

Golledge, R. G., Kwan, M.-P. & Garling, T. (1994), Computational-Process Modelling of Household Travel Decisions Using a Geographical Information System, Technical report.

Kitamura, R. (1984), 'A model of daily time allocation to discretionary out-of-home activities and trips', *Transportation Research Part B* .

Nurul Habib, K. M. & Miller, E. J. (2009), 'Modelling activity generation: A utility-based model for activity-agenda formation', *Transportmetrica* .

OFS (2015), Comportements de la population en matière de transports, Technical report, OFS.

Recker, W. W., McNally, M. G. & Root, G. S. (1986), 'A model of complex travel behavior: Part I-Theoretical development', *Transportation Research Part A: General* .

Recker, W. W. & Root, G. S. (1981), 'Toward a dynamic model of individual activity pattern formulation'.

Small, K. A. (1982), 'The scheduling of consumer activities: work trips.', *American Economic Review* .