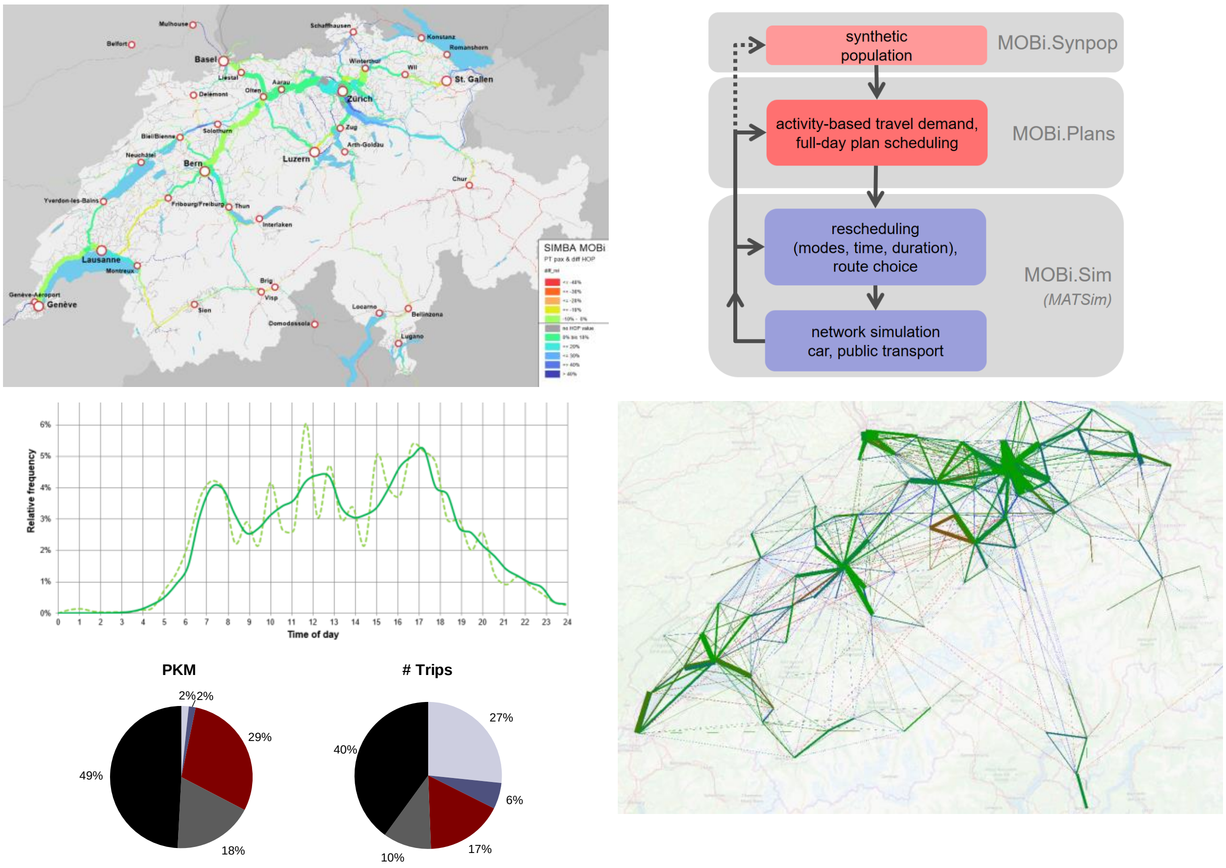

MOBi.plans: A Microscopic, Activity-Based Travel Demand Model of Switzerland.

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MOBi.plans: A Microscopic Activity-Based Travel Demand Model of Switzerland.

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Abstract

Travel demand models are used to predict traffic volumes on the infrastructure and user benefits from new service concepts. Most travel models which are applied in practice today simulate aggregated travel flows, i.e. they are of macroscopic nature. In contrast, we present a microscopic model, which simulates each traveller as an individual entity.

While learning from more than ten years of agent-based travel models of Switzerland, this model has broken new ground in two ways. First, the activity-based demand model is responsive to changes in travel supply, with all elements of an agent's plan (destinations, modes, times) reacting to changes in LOS. Secondly, as far as we know, this is probably one of the first microscopic model being developed, calibrated and applied inside a transport operating company.

This paper presents the activity-based travel demand module, called *MOBi.plans*. Starting from a synthetic population of Switzerland, *MOBi.plans* constructs individual activity and travel plans, balancing for each person preferences with constraints. Preferences are represented by a set of discrete-choice models for number of tours, number and kinds of activities, destination and mode choice. Constraints are represented in the plan adjustment and scheduling steps, using time budgets and a rule-based approach, which assures plan integrity and consistency.

At the time of the conference, the model will be finalized in the existing state. Full-day mobility plans are successfully fed into traffic flow simulation in *MATSim* and pilot applications on real world business cases have been run. The paper will explain functionality of different modules and give examples of calibration techniques. The road towards modelling corporate scenarios involving future mobilities will also be discussed.

Keywords

travel forecasting – national model – public transportation-operator – *SIMBA MOBi* – *MATSim* – *VISUM* – decision support – ridership forecast – microscopic – agent-based model– activity-based model – ABM

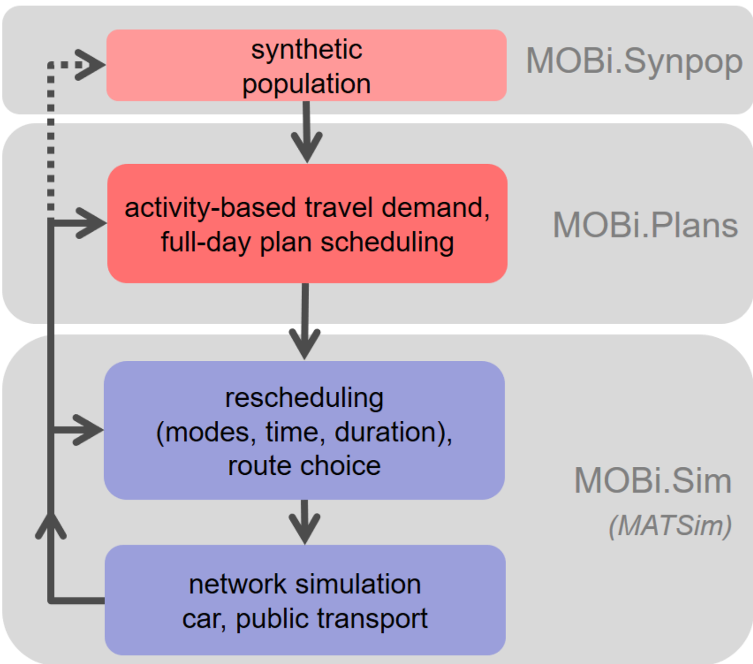
1. Introduction

1.1 The overall architecture of travel modelling at SBB

Transport modelling at SBB (Swiss Federal Railways) aims at supporting management decisions about future service concepts and investments in infrastructure and rolling stock (Scherr et al., 2018). To fulfil this mission, the SBB passenger division develops and maintains an aggregated rail-only travel model for over 15 years (Olesen et al., 2016).

A new simulation framework was required to be able to analyse future mobility schemes, including disruptive changes, new technologies, new intermodal services, such as mobility-as-a-service (MaaS) in competition or in combination with future rail service. For this purpose, SBB has developed over the past two years a microscopic activity-based model, called *SIMBA MOBi*. This model is person-based, simulates 24 hours of the average weekday and covers the entire country of Switzerland, with all-mode mobility, urban, rural and intercity. As far as we know, this is one of the first microscopic models that is developed and applied for business decision making inside a transport operating company in Europe.

Figure 1 *Overview SIMBA MOBi*



1.2 General model properties

A synthetic resident population of Switzerland, including households, persons, but also businesses and institutions as attractions (Bodenmann, 2014; Müller, 2017) is the starting point of the demand model. For the synthetic population, activity plans and travel plans are constructed for each person, balancing for each traveller both the individual preferences as well as constraints. Preferences are represented by discrete-choice models steps such as tour and activity frequencies, destination and mode choices. The scheduling step involves a rule-based approach, with constraints imposed to ensure consistency. Finally, 24-hour dynamic network flows for cars and public transport are simulated using the agent-based software *MATSim* (Horni et al., 2016).

The model is person-based. Household interaction is not modelled explicitly, choices of family members are not coordinated. However, household properties, such as size, presence of children or car ownership, are included into the person-based decision models. Hence, linkages between household members are modelled implicitly. For future scenarios we are working on modelling vehicle sharing of several agents in taxi services.

Software tools for this model are *MATSim*, *VISUM* plus own code extensions (mostly in Python and Java).

1.3 Overview of the paper

This paper focuses on the travel demand module *MOBi.plans*. The synthetic population (*MOBi.SynPop*) and the agent-based simulation model *MOBi.Sim*, which uses the *MATSim* software, are beyond the scope of this paper.

After the introduction (section 1), this paper starts out by presenting theory and practice of activity-based modelling (section 2). The main part of the paper gives a detailed description of the model's architecture and methodology (section 3) It is organized in subsections, starting with an overview (3.1), then explaining long term mobility choice (3.2), daily mobility choices (3.3) and rule-based scheduling (3.4). The section ends with short presentations of spatial discretisation (3.5) and agent-based network simulation (3.7). Validation results are presented in section 4. The paper closes with conclusions in section 5.

2. State of the art activity-based modelling

Since the origins of computer-based travel demand models in the 1960s until today, the mainstream of transportation planning models that are used in practice has been a macroscopic (i.e. aggregated) approach, based on several sequential steps (see Boyce and Williams, 2015). Later, the idea of activity-based transport models (ABM) emerged and was put into practice in the 1990s. For a historical review see Bowman (2009) or Rasouli and Timmermans (2014). Today there are several approaches of ABM, who differ in their focus and in terms of how far they have advanced to be used in real world applications. The following overview presents those ABM approaches that have influenced the authors in the development of *SIMBA MOBi*.

The North-American school of microscopic ABMs follows an econometric approach. Important representatives who have managed to get ABM up and running in practice for several major U.S. cities in the 2000s, are Bowman and Ben Akiva (2001), Vovsha, Bradley et al. (2004), Bhat et al. (2004). A comprehensive presentation of the methodology is given by Castiglione et al. (2015). We borrowed many concepts from this school for the generation of synthetic individual day-plans for each member of a population, using a system of discrete-choice models from the generation of tours and activities to the choice of modes, destinations and locations.

Other mainly academic ABMs can be defined as rule-based. We have drawn ideas from the work of Roorda et al. (2008) for plan scheduling. We found few sources regarding the implementations of time budgets in travel demand models; a rare example is Moeckel et al. (2019), using budgets of travel time.

Agent-based models emerged in the 2000s with a focus on large-scale and network-wide microscopic traffic simulation. SIMBA MOBi applies the open source software *MATSim* (Horni et al., 2016), which for over a decade has been in use to model Switzerland for research purposes (Meister et al., 2008). *MATSim* connects supply and demand in a network equilibrium. In addition to route search, agents can also reschedule time and mode choices. The *MATSim* software does not yet include modules to generate daily activity plans.

An earlier practice of tour-based models (Axhausen, 1989; Fellendorf et al., 1995) has a record of many real-world applications already in the 1990s, mainly in German-speaking countries. It was made available as part of the commercial *PTV VISUM* software. The aggregated calibration methodology of this approach was adapted for *MOBi.plans*.

Building on all the approaches mentioned above, we developed a model that is activity-based and microscopic and at the same time responsive to socio-economic shifts and to changes in transport supply through all model steps.

3. Model architecture, methods and computational flow

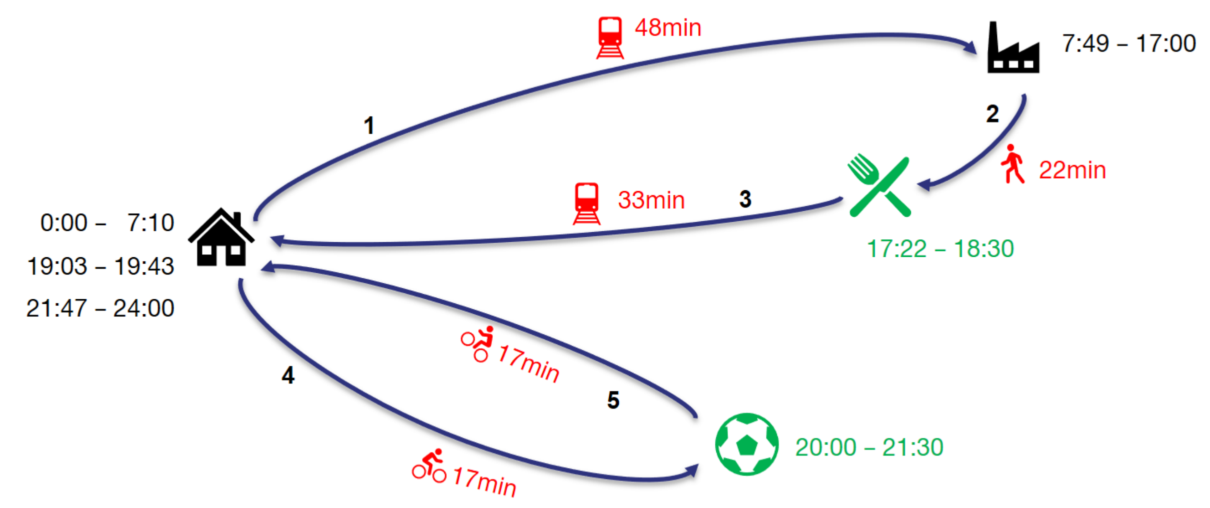
3.1 Overview

The objective of *MOBi.plans* is to synthetically generate an individual daily plan for each resident of Switzerland, as represented in the synthetic population. Each individual plan contains:

- the permanent location of primary activities, which are work and education, i.e. workplace and/or educational institute
- the desired number and kind of activities a person wishes to perform in a day
- the pattern of how those activities are bundled in tours
- the sequence of tours and the sequence of the activities within each tour
- the exact geographic location where each activity will be performed
- the mode choice for each tour or subtour
- the duration and time of day for each desired activity

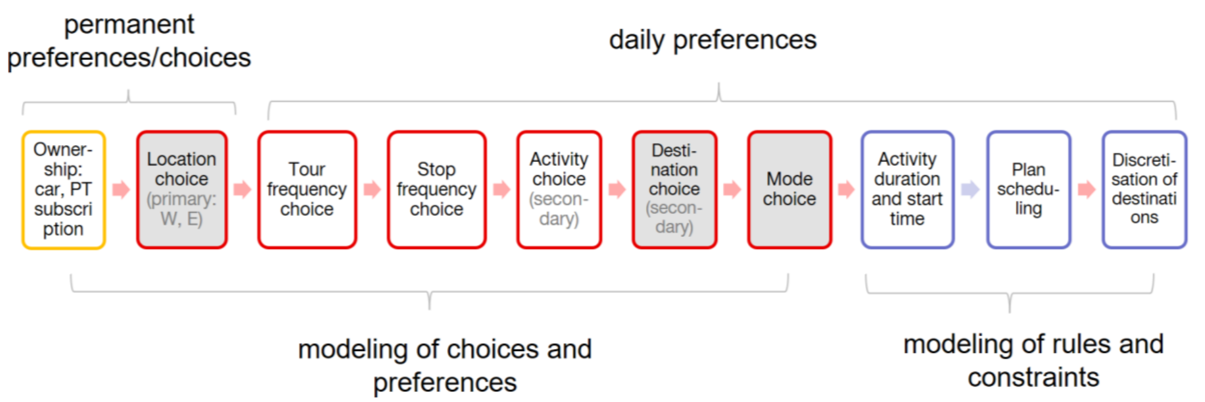
The Figure below visualizes an example of a plan with all its components.

Figure 2 *Example of a full-day plan with all its components*



The following Figure 3 shows how all these mobility choices are simulated by a sequence of model steps. These steps construct the individual plans starting with long-term choices, followed by daily choices, with the final steps being plan scheduling and discretisation. Technical details of each of these steps will be described later in the paper.

Figure 3 *MOBi.plans model steps*



3.2 Long term mobility choices

3.2.1 Car availability and PT subscription

A first model step determines car availability and PT subscriptions (i.e. yearly or monthly public transport passes) for each person in the population. Both are very important person attributes that have a strong impact on mode choice and destination choice. In the existing case these attributes are determined by choice models and then corrected based on small-area control variables (Danalet and Mathys, 2018). For the application of the model in forecasting the integration of accessibility measures to predict mode availability is planned.

3.2.2 Location choice

Location choice is defined as a decision about permanent locations such as work or school place of each individual agent. This decision is mainly constrained by the home place, person specific preferences and transport supply (LOS). In contrast to many other activity-based models (Castiglione et al., 2015), we compute location choice probabilities in a first step in an aggregated way, i.e. on traffic analysis zones (TAZ) and segmented by person groups. This method has the main advantage in its simplicity and of allowing for the use of established calibration methods. From these pre-computed probabilities, we later turn to microscopic modelling and each agent chooses its individual TAZ according to the Monte Carlo method.

Being responsive to changes in the LOS is a crucial requirement of the model. Hence, a nested model structure informs the location choice about the resulting “logsum” (or maximum expected utility) of the trips-based mode choice, capturing effects of the LOS. One major challenge is the replication of the nonlinear decrease in distance with the exponential form of the Logit model. As done in earlier studies, a piecewise-linear form of the distance term is used to more accurately capture this nonlinear effect. The LOGIT formula of location choice is identical to the one used in destination choice (see 3.3.2).

Additional additive utility terms (shadow prices) in the higher level of the location choice explain preferences, which cannot be explained by physical attributes of travel nor by LOS. In Switzerland, a classic example are language barriers which indicate substantial barriers in travelling as well.

3.3 Daily mobility choices

3.3.1 Tour and activity generation

The aim of tour- and stop frequency generation in combination with activity choice is to determine how many and which activities an agent performs during the day, as well as how those activities are combined in tours.

A tour is defined as a sequence of trips that begin at home and end there again. Our model does not allow for ending a tour at location different from home. Four different types of tours are modelled, the first two being considered primary tours and the latter two secondary tours:

1. Work tour
2. Education tour
3. Business tour
4. Other tour

A stop is a secondary activity, that is performed during a tour. The stop frequency choice model determines the number of stops made within a tour. For primary tours, stop frequency is segmented into:

1. An outbound stop model, which estimates the number of stops made between leaving home and the first primary activity (work or education).
2. A subtour model, that estimates whether there is a primary location-based subtour or not. A subtour is a sequence of trips that begins and ends at the primary location without going home. An example of a subtour is “work – leisure – work”.
3. An inbound stop model, that looks at the number of stops made on the way back home from the primary location.

For secondary tours, stop frequency is not segmented into different choice models. A single MNL determines the number of activities during a secondary tour.

After having made all the choices about number of tours as well as the number of stops during one tour, every person has a desired activity pattern containing number of activities as well as their order within a tour. Yet, this activity pattern does not contain information about destinations and time of day. Also, the order of the tours will be defined later.

Tour and stop frequency choices are organized as sequence of multinomial LOGIT models (MNL). The MNL coefficients were estimated using Biogeme (Bierlaire, 2016), based on data of the national travel diary survey (Federal Statistical Office, 2017). The dependent variable is the number of tours, subtours or stops, respectively. The endogenous variables are socio-economic variables plus spatial and accessibility measures. An overview of all models is given in Table 1. Examples of estimated parameters are shown in the appendix (Table 3 and Table 4). The perhaps most important property of the generation models is their ability to forecast changes in the mobility of individuals in reaction to mode availability, to changes in transport supply (by means of accessibility) and to demographic shift (by means of the age variable).

Table 1 *Overview: MNL models of Tour- and Stop Frequency*

	Tour frequency				**Sub tour frequency**	**Stop frequency**		
	Number of primary tours		Number of secondary tours		On primary tour	Number of stops on primary tour		Number of stops on secondary tour
	Work	*Education*	*Business*	*Other*		*Outbound*	*Inbound*	
Constant	X	X	X	X	X	X	X	X
Employment level	X	X	X	X	X	X	X	X
Main occupation is student/pupil		X		X	X			
Age	X	X	X	X	X	X	X	X
Is in management			X					
Presence of kids in HH (<18)	X			X	X	X	X	X
Car available	X		X	X	X	X	X	X
Public transport subscription	X	X	X	X	X	X	X	X
Car distance to primary location	X	X	X			X	X	
Number of total tours					X	X	X	X
Number of primary tours				X				
Is a work tour					X	X	X	
Is a business tour								X
Accessibility home location	X	X		X		X	X	X
Accessibility work/edu location			X		X			

Once the number of tours and their stops are calculated, the type of activity is added by applying probabilities differentiated by person groups resulting from travel diary evaluations. The following activity types are possible:

- Leisure (L)
- Shopping (S)
- Business (B)
- Education as secondary activity (EC)
- Accompany (A)
- Other (O)

3.3.2 Destination and mode choice

Knowing precisely number and type of activities each agent performs in each tour, the next step is choosing the destination of each secondary activity and the mode for each trip between activities. For this purpose, destination probability matrices for each activity type and different demand strata are estimated following the same method as in location choice (see 3.2.2).

The probability of choosing mode m on the origin-destination pair ij is:

$$P(m|ij) = \frac{exp(V_{ijm})}{\sum_k exp(V_{ijk})}$$

The expected maximal utility (EMU) of mode choice is then:

$$EMU_{ij} = \ ln\left\{\sum_m \left[exp(V_{ijm}/\theta)\right]\right\}$$

Mode choice depends on various variables such as travel time, distance and other level of service measures (see Table 2). To inform destination choice about the level of service of all modes**,** mode choice is nested into destination, by including EMU_{ij} (the expected maximal utility of mode choice) into the destination choice utility:

$$V(j|i) = ln(A_j) + \ \theta \cdot EMU_{ij} + \lambda_j + \lambda_{ij}$$

With:

- EMU_{ij}: maximum expected utility of mode choice from i to j
- A_j : = the socio-economic attraction of zone j
- λ_j := shadow price of destination j
- λ_{ij} := shadow price of origin-destination pair ij

For calibration purposes, it is important to extend the destination utilities with shadow prices. Finally, the probability of choosing destination j under the condition of starting in origin i is:

$$P(j|i) = \frac{exp(V(j|i))}{\sum_k [exp(V(k|i))]}$$

However, choosing the exact destination for each stop is not as straight forward as in location choice. Since an intermediate tour stop lies between two pre-defined locations, “rubber banding” is used to consider both trip origin i and primary location k (work or school place) in the choice of intermediary destinations. The rubber banding formula uses a weight α to balance the influence of primary locations and secondary destinations:

$$P(j|i) = \ \alpha \ \cdot P(j|i) + \ \ (1 - \alpha) \ \cdot P(j|k)$$

Table 2 *Variables used in mode choice utility*

mode	constant	travel time	access/egres (parking search) time	service frequency	number of transfers	parking cost	distance
walk	x	x	-	-	-	-	-
bicycle	x	x	-	-	-	-	-
PT	x	x	x	x	x	-	x
car - driver	x	x	x	-	-	x	x
car - passenger	x	x	x	-	-	x	x

Note that at this stage of the model, there is no interaction between the destination choice decisions of multiple tours. In some cases, this might result in unrealistically high travel time which violates time budgets and hence plan integrity. This issue will be treated at a later model stage (see 3.4.2).

The mode choice parameters calibrated for the nested mode and destination choice are trip-based. Parameters are estimated for the variables as depicted in Table 2. In the final mode choice step, the constraints of mode use along the tour are considered. A mode is assigned to each tour and subtour. The mode choice later informs the scheduling step (see 3.4.3) about the expected travel times. It is important to note that the tour-based mode choice calculated in this step, is the starting point for the agent-based traffic flow simulation (see 3.7) when modes will be reviewed and adjusted according to the network conditions each agent faces at the exact points in time and space of travel.

3.4 Rule-based scheduling

The rule-based scheduling solves the problem to fit all activity and travel episodes that were chosen in the previous steps into a consistent day-plan. It can be subdivided into three steps:

1. For each activity, durations are assigned (3.4.1).
2. Then, plans are revised to be consistent with time budgets (3.4.2). Revision means adjusting both destinations and activity durations during an iterative process.
3. Finally, the actual schedule procedure defines the starting time for each activity (3.4.3). During the final step, travel times and activity duration are not changed anymore.

3.4.1 Desired activity durations and activity start times

In a similar approach to the one taken by Hörl (2017), the activity durations are determined with probability distributions that have been derived from the travel diary. Also, the distributions of desired activity start times have been established, based on the diary survey.

The distributions for both, activity duration and start time, distinguish between several demand segments that are defined by:

- the type of activity
- socio-economic attributes of the person
- the frequency of an activity in one plan (e.g. the workplace is visited once or twice)

Figure 4 *Probability distributions of desired activity duration*

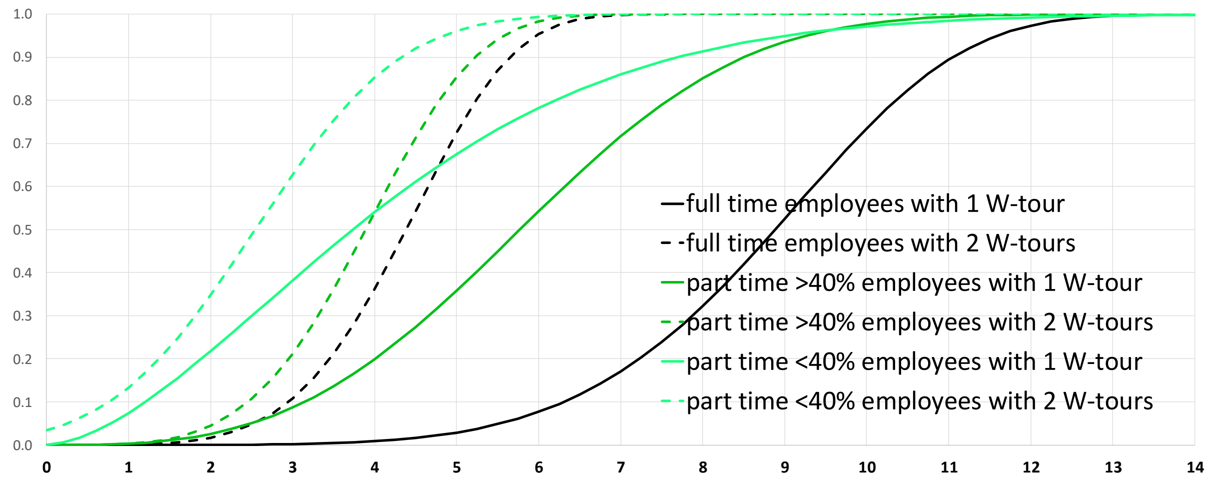
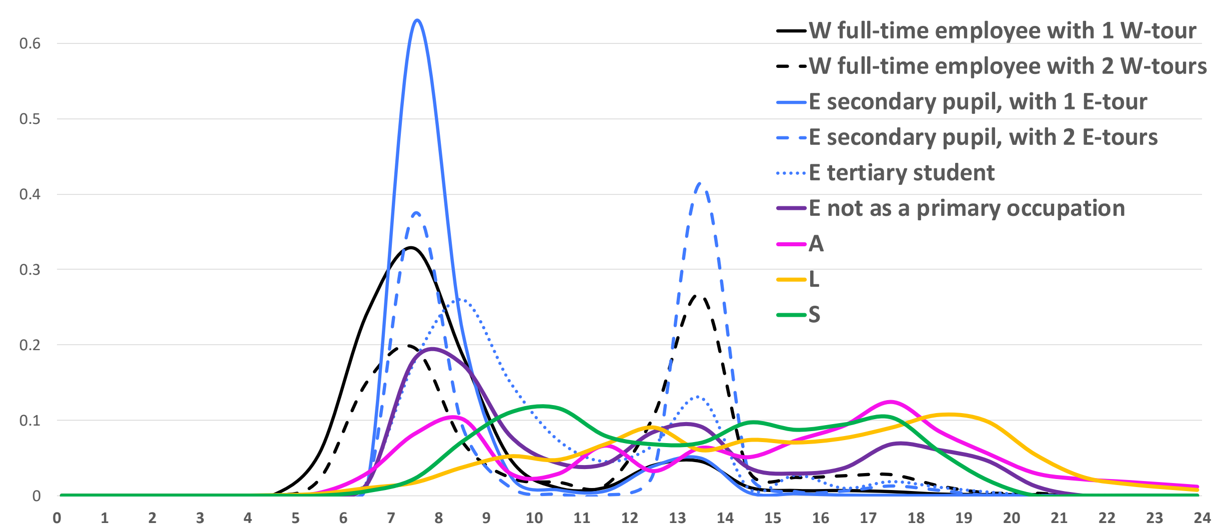


Figure 5 *Probability distributions of activity start times*



3.4.2 Adjustment of plan components based on time budgets

At this point, each person chose number of activities, destinations as well as activity duration based on preferences. However, some persons might have the preference to be extremely active during a day or vice versa. This model step reviews those kinds of plans and aims to make them more consistent (i.e. shorter distances as the number of activities increases) by comparing desired total times spent on travel and activities with time budgets.

The integrity of the plan requires that each plan must fulfil the following constraints:

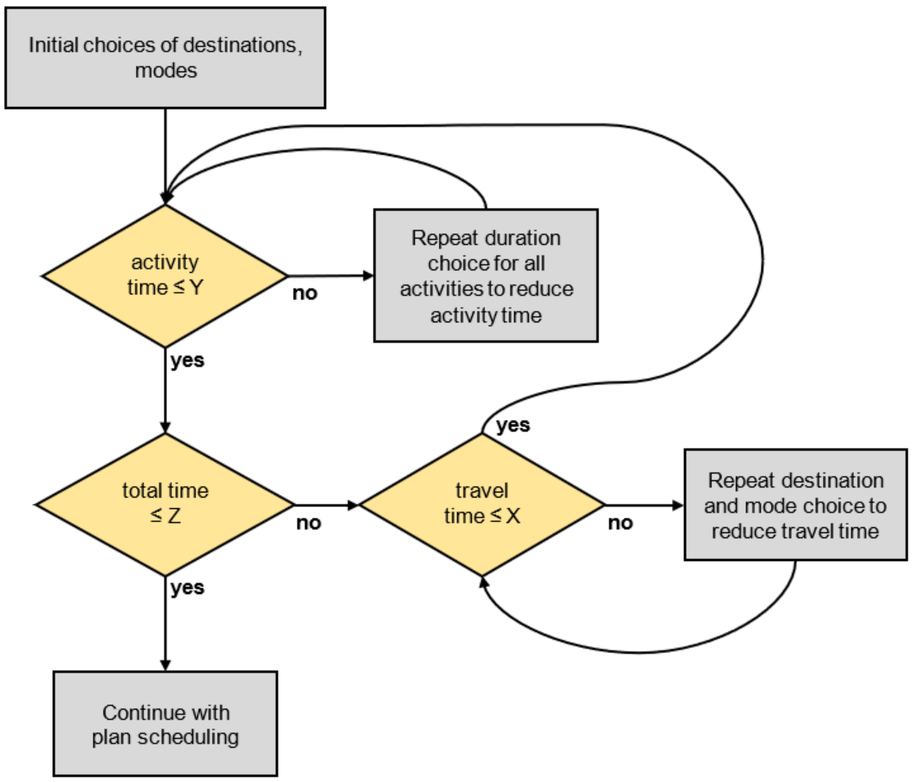
1. All activities must start between the hours of 0:00 and 24:00 (apart from the last home activity).
2. An agent can perform one activity or one trip at a time only.
3. The total of travel time shall not exceed the time budget X.
4. The total of activity time shall not exceed the time budget Y.
5. The total time spent on activity and travel episodes shall not exceed the total time budget Z, with Z = X + Y.

While constraints 1 and 2 will be enforced in the scheduling step (section 3.4.3), the step of plan adjustment ensures that constraints 3 through 5, i.e. the time budgets are satisfied. To satisfy the time budgets, the following changes can be performed:

- Redo the step of activity duration choice and so modify the durations of all activities.
- Redo the step of destination choice with the aim to obtain travel times that fit into the travel time budget.

The following figure shows a simplified view of plan adjustment:

Figure 6 *Rule-based plan adjustment algorithm*



We observed that 83.5% of the persons do not need an adjustment of the original preferences in their respective plan. Of the 16.5% who need adjustment, 8.2% adjust only activity durations, while the other 8.3% adjust also their destinations and modes. Note that the permanent locations of work and school places) are not adjusted. Only the destinations of secondary activities, which are considered day-to-day choices, are reviewed.

3.4.3 Scheduling procedure

Input for the scheduling procedure are the activity chains (the sequence of activities in each tour), and the durations of all activities from step 3.4.2. Travel times between activities are looked up for each individual trip depending on its mode.

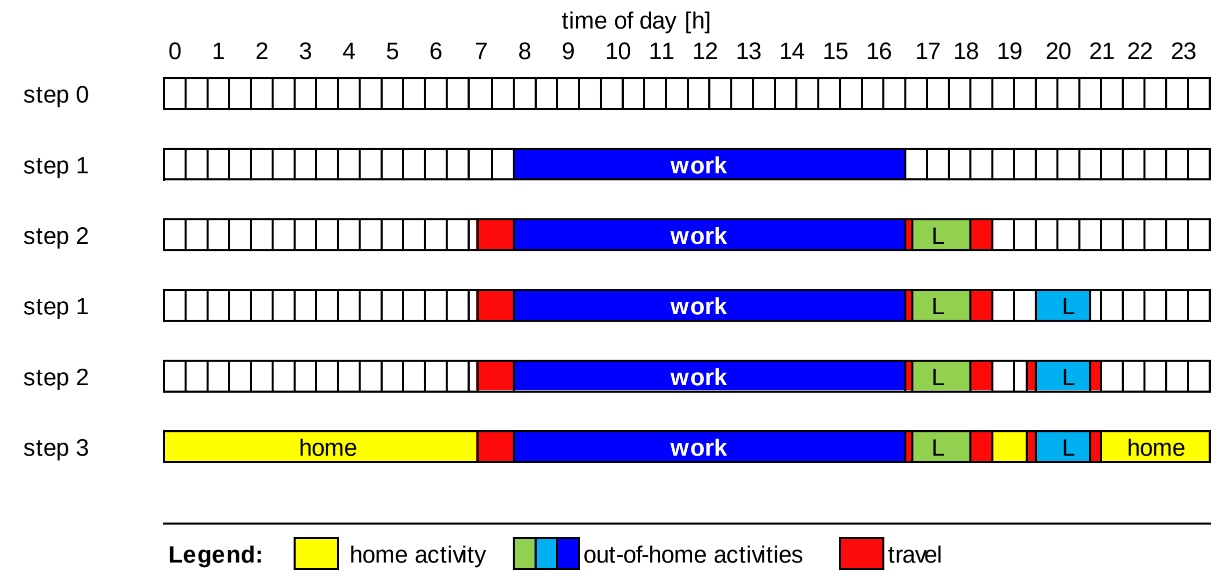
With these inputs given, the scheduling procedure then follows the principle of the "outward" approach described in Castiglione et al. (2015), with the rationale that priority is given to the primary activities and their durations, and that secondary activities and travel episodes are added before and/or after the primary activities. The procedure is given here in a simplified form:

> *Order the activity chains according to priorities*
>
> *Repeat min. m and max. n times:*
>
> > *For all tours:*
> >
> > > *"Step 1":*
> > >
> > > > *Choose start time for the primary activity (or main activity)*
> > > >
> > > > *Block time slots needed for the duration of primary activity*
> > >
> > > *"Step 2":*
> > >
> > > > *Block time slots needed for travel times to/from secondary activities*
> > > >
> > > > *Block time slots needed for duration of secondary activities*
> > >
> > > *Between tours, block a minimum of 30 minutes for the home activity*
> >
> > *Compute objective function depending on time-of-day probability distributions*
> >
> > *Keep schedule if it has a higher objective value than previous best schedule*
> >
> > *If reached m and all activities start between 0:00 and 24:00: break*
> >
> > *Else: continue*
>
> *If not succeeded (exceeded n): discard the lowest tours in the priority order.*
>
> *"Step 3": assign all remaining time slots to the home activity"*

The above algorithm will discard tours from the schedule, if they do not fit into the 24 hours of the day. This is the last resort to assure integrity of the plans. But these cases are extremely rare (less than 4 ‰ of all trips), thanks to the step of plan adjustment (3.4.2), that is effective to assure that the timing constraints can be met by the scheduling procedure.

Figure 7 below illustrates the scheduling procedure for the example that was given earlier in the paper (Figure 2):

Figure 7 *Example of the rule-based plan scheduling*



3.5 Spatial discretisation

After the scheduling step, all plans are precise in time. Start and end times of activities and travel times are given in hours, minutes and seconds of clock time. The spatial precision however is still mixed at this time. While home locations have precise coordinates, locations of primary and secondary activities are still based on the 8000 zones that were used in location and destination choice.

In the final step of the demand model, the activity locations are broken down from zones to geographically precise coordinates. The synthetic population provides facilities, which can be businesses, other institutions or households. These facilities are precisely geo-coded. The discretisation step choses randomly for each activity of each agent one facility among all facilities in the destination-zone that are open for the respective activity. The random draw respects weights which correspond to the attractions A_j in destination choice: e.g. number of jobs in a work facility for activity work, school enrolment for education, number of jobs in retail for shopping.

We feel that this discretisation method is very effective for our model: The zonal system, which was defined by the Swiss Federal Government for travel modelling purposes, has a fine granularity with in average 1000 inhabitants. In urban areas, zones are small and accessibility to the transport network is homogenous across the zone, and hence random distribution of destinations can be independent of mode availability. In rural zones with less density however, there are significant differences of accessibility between the facilities within one zone. E.g. destinations can be 50m or 2000m from the next public transport stop. But, land use policies in Switzerland require facilities to be concentrated “in the village”, which is realistically represented in our synthetic population, and public transportation stops are also always located in the village center. Still, some agent’s plans who have chosen public transportation will obtain a destination of the trip that is not suitable for this mode. In that case, mode choice will be corrected during agent-based traffic flow simulation (see 3.7).

3.6 Complementary exogenous travel demand

The activity-based demand model covers the travel of the resident population of Switzerland. To produce comprehensive traffic on the networks, exogenous demand is developed from the best available sources. The exogenous demand includes international rail travel, border crossing road traffic, airport travel by non-residents, travel by tourists and visitors (both road and rail).

3.7 Agent-based network simulation

Endogenous plus exogenous demand - in the form of full-day plans - are fed into the agent-based network simulation *MATSim*, which implements a spatially fully disaggregate multimodal assignment (Horni et al., 2016). For our model, the network simulation was built based on the experience of earlier academic *MATSim* models of Switzerland (Meister et a., 2008; Boesch et al., 2016), then in-house calibrated by SBB (Scherr et al., 2018; Rieser et al., 2018). Agent-based network simulation has the following practical consequences for the activity-based demand model *MOBi.plans*:

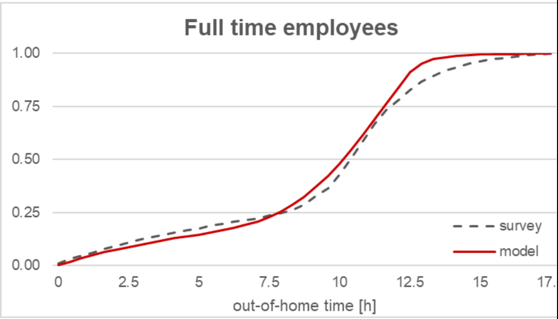
- Agent-based simulation requires strong plan integrity: one person can only perform one activity or one trip at a time, a challenge that is solved in the scheduling step. Other ABMs, that feed into aggregated assignment models, often ignore this requirement.
- From the simulation model we also derive LOS-indicators. While they are computed from/to discrete geo-codes, we aggregate them from/to zones for *MOBi.plans*.
- In *MATSim*, each agent faces his/her individual network conditions. The agent can adjust their daily plan in some of the choices (mode, activity duration, departure time). This allows for compensation of generalisations that were caused by the zonal aggregation of the LOS indicators.

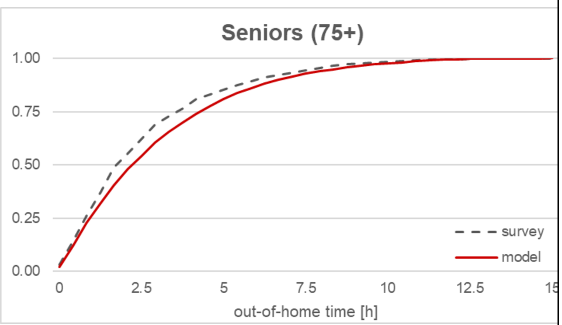
4. Model validation

The model is validated in comparison to comprehensive travel statistics that include the national travel diary survey, national rail OD-survey, rail counts, other public transportation counts, road traffic counts, and SBB corporate data (see Figure 8). In the following we show a few examples of validation that are preliminary results, as at the time of this paper's submission the calibration has not yet been completed.

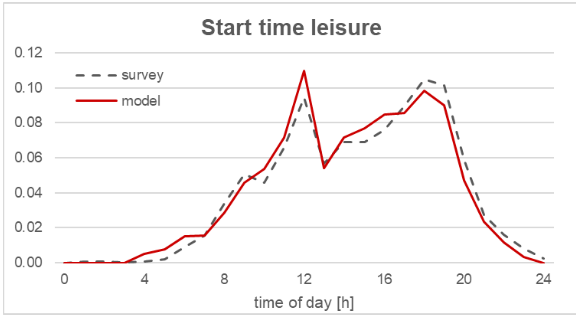
Figure 8 *Examples of model validation*

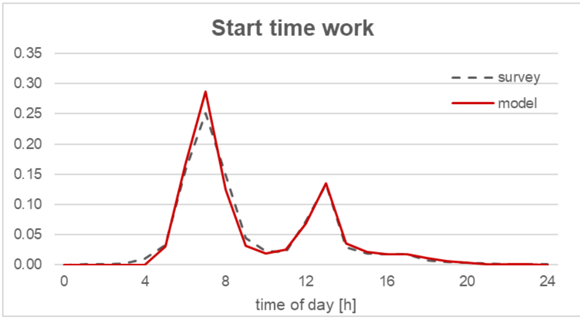
Total out-of-home time per capita



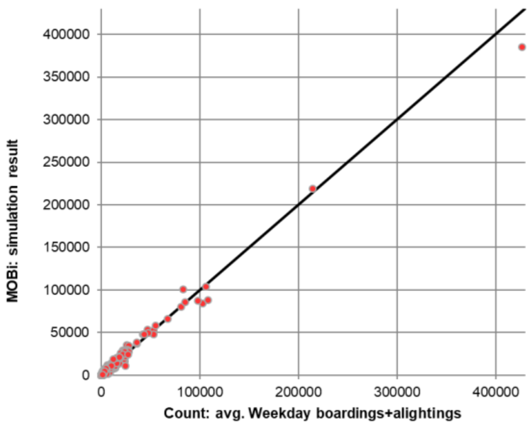


Time of day distribution of travel

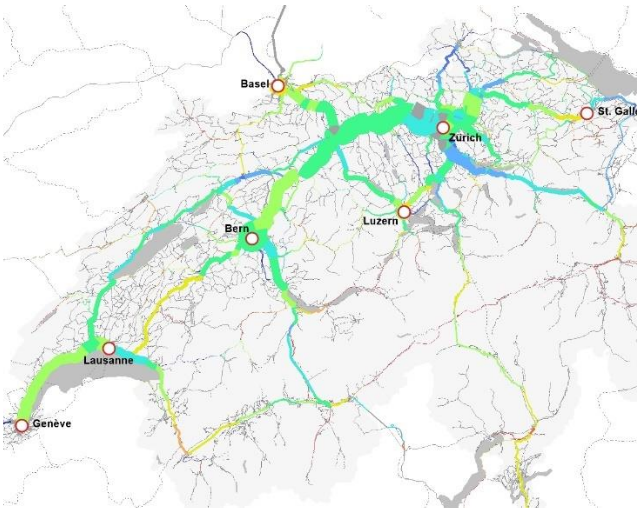




Boarding & alighting at rail stations



Passenger volumes, rail network



5. Summary and conclusions

At the time of the conference, model calibration is finalized in the existing state.

5.1 Summary: main properties of the model

The properties of the model SIMBA MOBi can be summarized as follows:

- Activity-based approach
- Microscopic simulation through all model steps: from generation to network flow simulation
- High resolution of time and space
- Use of aggregated zones in intermediary steps, while the final demand has exact geographic locations for all destinations in a plan
- Person-based simulation, taking household properties in consideration in persons' decisions, but not modelling household interactions explicitly.
- Representation of 24 hours of the average weekday
- Strong integrity of the time and space sequence of activities and travel along 24-hour plans
- A focus on the representation of variables (person attributes and transport LOS) that explain travel choice for or against public transportation.
- A strong effort in model calibration to allow for the analysis of travel volumes and capacities on a transportation project level.

5.2 Conclusions

Based on our experience we state that microscopic activity-based models are ready for practice. We have achieved model calibration to a goodness of fit as it is expected in the practice of macroscopic models. Microscopic models today require more staff time and computer resources than conventional models. Some of the reasons are: complexity of the approach, increased amount of data and parameters, software tools still being under development in terms of functionality and user friendliness. We continue to work on improving usability and computational efficiency. On the other hand, there is a lot of benefit from microscopic modeling. The high geographic and socio-economic granularity of travel demand allows for analyses that were unthinkable with conventional models. Among those are: traveler composition according to multiple attributes, coverage of all legs of travel from door to door, time-dynamic outputs over 24-hours, analysis of all public transportation stops without the limitation to major stations. Further, we expect increased possibilities in forecasting future mobilities: Agent-based traffic flow simulation enables the integration of new travel modes and the activity-based demand model allows for changes in activity and travel patterns of future populations (e.g. "active seniors" perform more activities and longer trips than the same age group does today).

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Appendix – estimated models

Table 3 *LOGIT coefficients: choice of **tour frequency** of "Other Tours"*

	Number of other tours per day 0	1	2	3
Constant	0.000	+1.861***	+1.603***	-0.140
Employment level = 0%	0.000	+0.051	-0.229	-0.276
Employment level 1%-39%[1]	0.000	-0.008*	-0.011*	-0.007
Employment level 40%-79%[1]	0.000	-0.014***	-0.017***	-0.026***
Employment level >= 80%[1]	0.000	-0.005*	-0.017***	-0.020***
Age < 18[1]	0.000	-0.022	-0.047*	-0.038
18 <= age < 25[1]	0.000	-0.078***	-0.059***	+0.059*
25 <= age < 65[1]	0.000	-0.002	-0.000	-0.003
65 <= age < 75[1]	0.000	-0.019*	-0.016	-0.061***
Age > 75[1]	0.000	-0.048***	-0.091***	-0.099***
Presence of kids in the HH (<18)	0.000	+0.035	+0.256***	+0.554***
Is student	0.000	-0.726***	-0.625***	-0.882***
Is apprentice	0.000	-0.390***	-0.154	+0.303
Is pupil	0.000	-0.727***	-0.587***	-0.453
Car available	0.000	+0.452***	+0.854***	+1.053***
PT subscription	0.000	-0.094**	-0.141***	-0.230***
Number of primary tours	0.000	-0.807***	-1.850***	-2.566***
Number of total tours				
Tour is a business tour				
Car distance primary location				
Accessibility (home, multimodal)	0.000	+0.023***	+0.039***	+0.032*
Accessibility * car_available[2]	0.000	-0.035***	-0.032***	-0.015***

Number of observations : 38149

Rho-square : 0.22

[1] piecewise linear variable

[2] interaction term of 2 variables

* *P ≤ 0.05*

** *P ≤ 0.01*

*** *P ≤ 0.001*

Table 4: *LOGIT coefficients: choice of* ***"stop frequency"*** *(secondary activities) on "Other Tours"*

	Number of stops on an "Other Tour" 1	2	3	4
Constant	0.000	-2.645***	-4.060***	-5.590***
Employment level = 0%	0.000	-0.108	-0.375*	-0.065
Employment level 1%-39%[1]	0.000	-0.006	-0.011*	-0.003
Employment level 40%-79%[1]	0.000	+0.004***	+0.006	+0.005
Employment level >= 80%[1]	0.000	-0.016***	-0.015**	-0.011
Age < 18[1]	0.000	+0.057***	+0.104***	+0.132***
18 <= age < 25[1]	0.000	+0.012*	-0.008	-0.010
25 <= age < 65[1]	0.000	-0.003	-0.004	-0.005
65 <= age < 75[1]	0.000	+0.003	-0.005	-0.040*
Age > 75[1]	0.000	-0.003	-0.027	-0.025
Presence of kids in the HH (<18)	0.000	+0.001	+0.016***	-0.011
Is student				
Is apprentice				
Is pupil				
Car available	0.000	+0.003	+0.088	+0.269**
PT subscription	0.000	+0.123**	+0.281***	+0.489***
Number of primary tours				
Number of total tours	0.000	-0.006***	-0.007***	-0.007***
Tour is a business tour		0.845	1.800	1.980
Car distance primary location				
Accessibility (home, multimodal)	0.000	+0.018***	0.000	0.000
Accessibility * car_available[2]				

Number of observations : 37503
Rho-square : 0.468

[1] piecewise linear variable

* *P ≤ 0.05*
** *P ≤ 0.01*
*** *P ≤ 0.001*