Enhancement and empirical estimation of MATSim's utility function

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1   Abstract

The agent-based micro-simulation toolkit MATSim implements an activity-based approach to travel demand generation for large samples. A co-evolutionary learning process assigns every agent with an all-day activity-travel schedule. The schedule holds information on which activities the agent performs, in which order, where and for how long, and which travel modes the agent uses between the activities including corresponding routes. This paper proposes a new MATSim utility function for the performance of activities, based on an asymmetric S-shaped curve with an inflection point. The new utility function can cope with a flexible number of activities in a schedule as it formulates an optimal activity duration by its functional form. It has become necessary since a new algorithm was added to MATSim's replanning step that comprehensively optimizes schedules, including their activity chain sequences. This paper further presents a methodology to empirically estimate the parameters of the new utility function through an enhanced Multinomial Logit (MNL) model. A similarity attribute in the systematic part of the utility function allows to overcome the MNL model's IIA property. First estimates of a limited set of parameters are presented although the results are still preliminary and ambiguous.

2   Introduction

The agent-based micro-simulation toolkit MATSim implements an activity-based approach to travel demand generation for large samples. A co-evolutionary learning process assigns every agent with an all-day activity-travel schedule. The schedule holds information on which activities the agent performs, in which order, where and for how long, and which travel modes the agent uses between the activities including corresponding routes.

MATSim is a utility-based simulation model, i.e. the optimality, or fitness, of a schedule is measured against its utility. Optimizing a schedule means to maximize its utility. MATSim's existing utility function has become problematic in two aspects:

- MATSim's existing utility function features a log form for the performance of activities (Charypar and Nagel, 2005). This results in unrealistic effects when changes in the number of activities of a schedule are allowed. When the number of activities in the schedule is a dimension of the learning process the log form leads to a lot of very short activities due to the decreasing marginal utility of the log-form. In other words, a schedule of two 30 minutes activities of a certain type is always better than a schedule of once 60 minutes of the same activity.

- The parameters of MATSim's existing utility function were set reasonably but arbitrar-

ily (Charypar and Nagel, 2005). They were not estimated empirically.

This paper presents a new utility function for the performance of activities, based on an asymmetric S-shaped curve with an inflection point as presented by Joh (2004). The new function can cope with a flexible number of activities in a schedule. Furthermore, a methodology is proposed to empirically estimate the parameters of the new utility function through an enhanced Multinomial Logit (MNL) model from Swiss Microcensus data.

The structure of the paper is as follows: Chapter 2 gives an introduction to MATSim, its core principles, and its existing utility function. The new utility function for the performance of activities is presented in chapter 4. Chapter 5 deals with the empirical estimation of the new function's parameters, including preliminary results for a set of most relevant parameters. The paper closes with a summary and outlook.

3   MATSim overview

MATSim[1] (Multi-Agent Transport Simulation, Balmer, 2007; Meister *et al.*, 2009; Balmer *et al.*, 2008a) is an activity-based transport simulation model for large samples. Unlike other transport simulation models, MATSim is agent-based throughout and produces individual activity schedules as input to the traffic flow simulation rather than origin-destination matrices as typically used in dynamic traffic assignment (Illenberger *et al.*, 2007). Initial demand schedules are generated by disaggregating census data. The schedules are executed and overall travel costs calculated using a suitable traffic flow microsimulation. Henceforward, the utility of the schedules is iteratively improved against the background of overall travel costs (see figure 1). Central to the improvement of the schedules is MATSim's replanning step where agents are allowed to learn and optimize their schedules. MATSim's existing replanning step features algorithms to optimize the location choices (Horni *et al.*, 2008), the route choices (Lefebvre and Balmer, 2007), and the mode choices together with the activity timings (Balmer *et al.*, 2008b). Since always a certain share (e.g., 10%) of the overall set of agents do so simultaneously MATSim's simulation process is a co-evolutionary learning process. The co-evolutionary learning process stops when none of the agents can further improve their schedule, or at an externally given maximum number of iterations. MATSim is developped jointly by TU Berlin, ETH Zurich and CNRS Lyon. It has been applied to several scenarios such as Switzerland, Berlin-Brandenburg/Germany, Toronto/Canada, Padang/Indonesia, among others.

The optimality of a schedule is measured against its utility. Optimizing a schedule means to maximize its utility. In MATSim, the problem of maximizing a schedule's utility is expressed

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[1]This chapter partly draws from Feil *et al.* (2009).

Figure 1: MATSim's process flow.
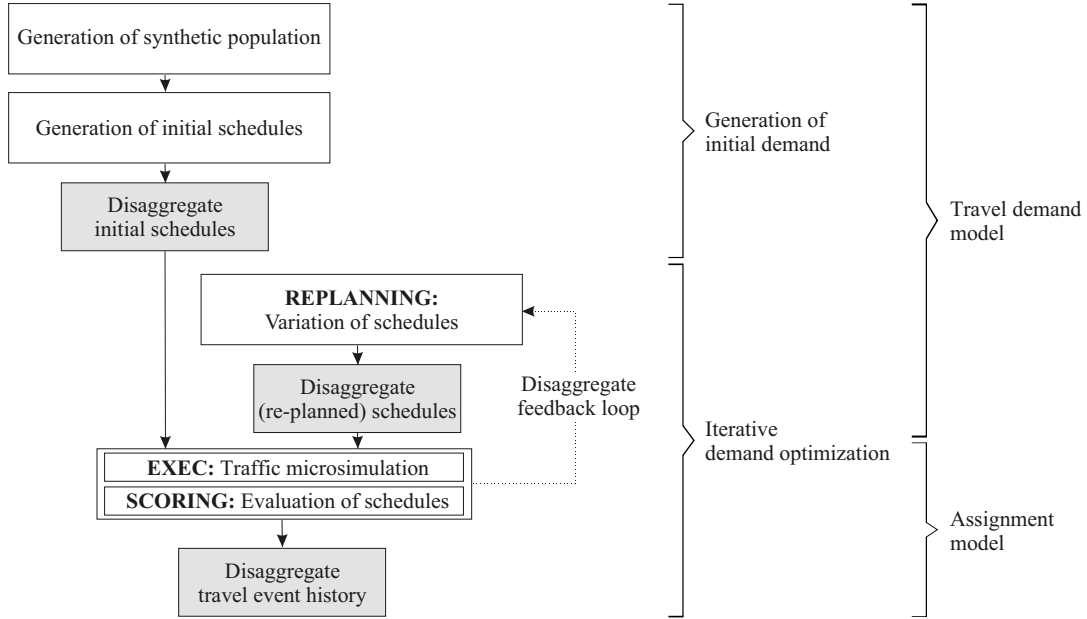
by the following objective function:

$$max\ U_{total,i} = max\left[\sum_{j=1}^{n} U_{perf,ij} + \sum_{j=1}^{n} U_{late,ij} + \sum_{j=1}^{n} U_{travel,ij}\right] \tag{1}$$

where $U_{total,i}$ is the total utility of the given schedule i; n is the number of activities/trips; $U_{perf,ij}$ is the (positive) utility gained from performing activity j; $U_{late,ij}$ is the (negative) utility gained from arriving late at activity j; and $U_{travel,ij}$ is the (negative) utility gained from travelling trip j. $U_{late,ij}$ and $U_{travel,ij}$ are linear functions. $U_{perf,ij}$ is a log function with a decreasing marginal utility the longer the activity is performed:

$$U_{perf,ij}(t_{perf,ij}) = \max\left[0, \beta_{perf} \cdot t_{ij}^* \cdot \ln\left(\frac{t_{perf,ij}}{t_{0,ij}}\right)\right] \tag{2}$$

where $t_{perf,ij}$ is the actual performed duration of the activity, t_{ij}^* is the "typical" duration of an activity, and β_{perf} is the marginal utility of an activity at its typical duration. β_{perf} is identical for all activities. $t_{0,ij}$ is defined as follows:

$$t_{0,ij} = t_{ij}^* \cdot e^{\frac{-A}{t_{ij}^*}} \tag{3}$$

where A is a scaling factor. $t_{0,ij}$ influences both the minimum duration and the priority of an activity. The smaller $t_{ij}^* - t_{0,ij}$ (while by definition $t_{0,ij} < t_{ij}^*$), the steeper the ascent of the log function between $t_{0,i}$ and t_{ij}^* and, thus, the higher the marginal utility will be. This implies that it is favourable to shorten other activities with lower marginal utility to ensure that this activity

time window can be kept. In the absence of externalities such as opening hours, the maximum utility over the activities of the schedule is reached when all activities have the same marginal utility.

4 New utility function for the performance of activities

4.1 Problem formulation

MATSim's replanning step features algorithms to optimize the location choices (Horni *et al.*, 2008), the route choices (Lefebvre and Balmer, 2007), and the mode choices together with the activity timings (Balmer *et al.*, 2008b). The maximum utility over the activities of the schedule is reached when all activities have the same marginal utility (s.t. externalities such as opening hours). A new algorithm *PlanomatX* has recently been introduced that optimizes also the activity chain sequence of the schedules (Feil *et al.*, 2009). The log form of the utility function for the performance of activities has now become problematic as it results in unrealistic effects. When the number of activities in the schedule is a dimension of the learning process the log form leads to a lot of very short activities due to the decreasing marginal utility of the log-form. In other words, a schedule of two 30 minutes activities of a certain type is always better than a schedule of once 60 minutes of the same activity. We therefore need a utility function for the performance of activities that can cope with a flexible number of activities in the schedule.
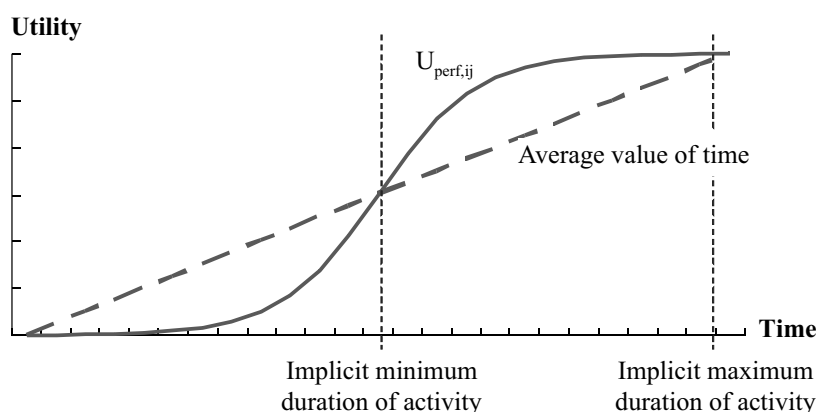
4.2 New utility function

Given the problem formulation, we require a utility function for the performance of activities that formulates an optimal activity duration by its functional form. Assuming an average value of time, the utility function should feature segments where its value of time is below the average value of time, and segments where it is above. The optimal activity duration will be found in the latter segments. Joh (2004) presents a utility function matching these requirements:

$$U_{perf,ij}(t_{perf,ij}) = U_{ij}^{min} + \frac{U_{ij}^{max} - U_{ij}^{min}}{(1 + \gamma_{ij} \cdot exp\left[\beta_{ij}(\alpha_{ij} - t_{perf,ij})\right])^{1/\gamma_{ij}}} \tag{4}$$

The function is an asymmetric S-shaped curve with an inflection point, originally developed in biological science (see figure 2). U_{ij}^{min} is the time-independent minimum utility of performing activity j of schedule i, and U_{ij}^{max} the time-independent maximum utility of performing activity j. α_{ij}, β_{ij} and γ_{ij} are parameters that influence the shape of the curve: α_{ij} indicates at what duration the function reaches its maximum utility U_{ij}^{max} ("inflection point"). β_{ij} influences the

Figure 2: Generic illustration of new utility function for the performance of activities.

slope of the function. γ_{ij} determines the relative position of the inflection point (see Joh, 2004).

For some first application tests, the new function has been assigned with a set of parameters trying to match MATSim's existing log utility function parameters (Feil *et al.*, 2009; Feil, Forthcoming). The tests have shown that the new utility function harmonizes well with PlanomatX. It relieves the disadvantages of the previous log form function.

5 Empirical estimation of the parameters of the utility function

5.1 Problem formulation

The parameters of both MATSim's existing utility function and of the new utility function for the performance of activities were set reasonably but arbitrarily (Charypar and Nagel, 2005; Feil *et al.*, 2009, see table 1). An empirical estimation of the parameters seems indispensable, particularly with respect to the increased complexity of the new utility function for the performance of activities.

5.2 Estimation methodology

We propose an iterative approach[2] to estimate MATSim's utility function parameters (see figure 3). First, relevant survey data is extracted and the choice set generated (step 1). Missing

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[2]Compare with other iterative parameter estimation approaches, e.g., Vrtic (2003), chapter 6; de Palma *et al.* (2007).

Figure 3: Estimation methodolgy of the utility function parameters.
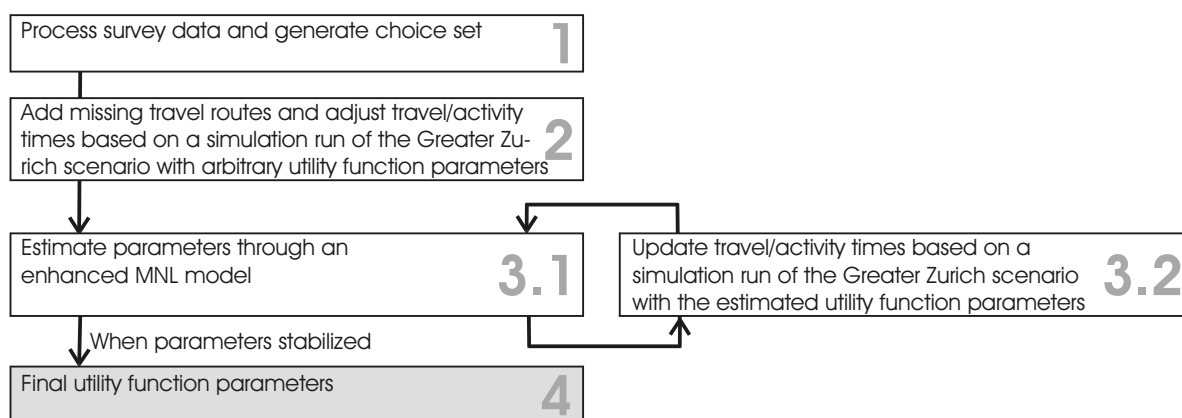
survey data is added using the results of a MATSim simulation run (step 2). The estimation of the utility function parameters (step 3.1) then alternates with the update of travel and activity times drawn from MATSim simulation runs with the estimated function parameters (step 3.2). Final (stable) function parameters should be produced after a couple of such iterations (step 4). The following sections will illustrate the methodology in more detail.

5.3   Processing survey data and generating choice set (step 1)

The estimation is based on revealed behaviour data of the Swiss Microcensus 2005 (national travel survey). The Microcensus comprises roughly 19,000 travellers for the whole of Switzerland. Slightly more than 4,000 travellers fall into the Greater Zurich area which is our study area. For the estimation of the parameters, every traveller requires a choice set comprising the chosen schedule and several non-chosen alternative schedules:

- *Chosen schedule*: The chosen schedule is obviously the schedule reported in the Microcensus. The Microcensus data set holds information on what activities each traveller performs, in which sequence, for how long, where, and which mode he uses to travel in-between the activities.

- *Non-chosen alternative schedules*: The non-chosen alternative schedules can be any schedules different from the traveller's chosen one. The only limitation is that the parameter and attribute vectors β_i and x_i of an alternative i must be consistent throughout all travellers (see model formulation, section 5.5). Under the assumption that we want to estimate, at this stage, the parameters for the performance/duration of activity types and for travel, we must ensure that an alternative i includes the same activity type sequence and the same travel modes throughout all travellers. It thus seems intuitive to assign a

traveller with the chosen schedule structures (activity types and modes) of the other travellers as his non-chosen alternative schedule structures, s.t. those schedule structures are different from his chosen one. The slightly more than 4,000 travellers of interest feature about 500 different schedule structures. We have reduced this number and selected the 60 most frequent schedule structures still representing 2,514 travellers. After copying the schedule structures the "inner activities"[3] are assigned with randomly chosen locations and durations. This is expected to generate a high variance in the travel and activity timings (see step 2), and a high variance is desirable for the estimation. The home location is copied from the chosen schedule.

Our data set for the estimation of the parameters thus comprises 2,514 travellers and every traveller holds one chosen schedule and 59 alternative schedules. Activity types and locations as well as travel modes have been assigned to the schedules. Step 2 will complete the schedules adding travel routes and activity/travel timings.

5.4   Adding travel routes and adjusting travel/activity times (step 2)

Both chosen and non-chosen alternative schedules still miss travel routes. The travel routes can be added using a MATSim simulation run of the Greater Zurich scenario with the existing (arbitrarily set) utility function parameters (see table 1; see Feil *et al.*, 2009, for description of scenario, further settings, and simulation results). The simulation results allow to define (approximate) fastest routes for both the chosen and non-chosen schedules. Along with the travel routes come the travel times and the effective activity durations (arrival time of previous trip until departure time of following trip). For the chosen schedules, the reported travel times may need to be updated if the simulated travel times differ from them. In this case, the simulated travel times and the corresponding activity timings are adopted in order to keep the model consistent.

5.5   Model formulation (step 3.1)

The estimation of the parameters is conducted using an enhanced Multinomial Model (MNL). The MNL model was first proposed by McFadden (1974). It assumes that the utility of an alternative i can be expressed as

$$U_i = V_i + \varepsilon_i \tag{5}$$

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[3]The "inner activities" are all activities except from the home activity which is, by definition, always a schedule's first and last activity.

Table 1: Step's 2 initial parameter settings.

Parameter	Value Home	Work	Education	Shopping	Leisure
Umax	60.0	55.0	40.0	35.0	12.0
Umin	0.0	0.0	0.0	0.0	0.0
alpha	6.0	4.0	3.0	2.0	1.0
beta	1.2	1.2	1.2	1.2	1.2
gamma	1.0	1.0	1.0	1.0	1.0

Parameter	Value
U_car	-6.0
U_walk	-6.0
U_pt	-6.0
U_late	-18.0
U_wait	-6.0

where V_i is the deterministic utility component and ε_i a stochastic error term. V_i is calculated as $V_i = f(\beta_i, x_i)$. β_i is the vector of (taste) parameters (the parameters to be estimated) and x_i the vector of the attributes of alternative i. The error term ε_i is assumed identically and independently (i.i.d.) Gumbel distributed. The choice probability of an alternative i from a given choice set C is then defined as:

$$P(i|C) = \frac{e^{\mu V_i}}{\sum_j e^{\mu V_j}} \tag{6}$$

μ is related to the standard deviation of the Gumbel variable ($\mu^2 = \frac{\pi}{6\sigma^2}$), where, in the absence of a heterogeneous population, μ is generally constrained to a value of 1 (Schüssler and Axhausen, 2007).

The MNL model is popular due to its ease of the parameter estimation (see e.g., Ben-Akiva and Lerman, 1985). It bears the disadvantage of the Independence from Irrelevant Alternatives (IIA) property. The relative ratio of the choice probabilities of two alternatives does not depend on the existence or the characteristics of other choice alternatives (see e.g., Schüssler and Axhausen, 2007, for more details). We have therefore enhanced our MNL model with a similarity attribute in the systematic part of the utility function:

$$V_{total,i} = \left[\sum_{j=1}^{n} V_{perf,ij} + \sum_{j=1}^{n} V_{late,ij} + \sum_{j=1}^{n} V_{travel,ij} + \delta_{sim} \cdot sim_{i,i'} \right] \tag{7}$$

The attribute $sim_{i,i'}$ reflects the structural similarity between the schedules following the logic of the path-size logit or C-logit approach. It is calculated using a Multidimensional Sequence

Table 2: Similarity results of chosen schedule and some non-chosen schedules of sample traveller 120451, based on Joh's Multidimensional Sequence Alignment Method.

|								Individual similarity value sim_i,i'k	Overall similarity value sim_i,i'
Chosen schedule									
home 123276	car	leisure 126614	car	leisure 113242	car	home 123276			
Non-chosen alternative schedules (excerpt)									
home 123276	pt	work 105797	pt	home 123276				6.0 5.0 3.0	8.0
home 123276	car	shopping 106984	car	home 123276				6.0 1.0 3.0	6.0
home 123276	pt	work 106760	walk	shopping 111632	walk	work 106760	pt	home 123276	10.0 7.0 5.0	12.0
home 123276	pt	work 110590	pt	home 111672	pt	leisure 110907	pt	home 123276	6.5 7.0 5.0	10.0

⋮

Σ = 59

Alignment Method (Dynamic Programming Approach, see Joh *et al.*, 2002; Joh, 2004) that, in our case, considers the similarity between the chosen schedule and the non-chosen alternative schedules along the activity chain sequence, mode choice, and location choice dimensions. Determining the similarity values of the schedules of our choice set (see example in table 2 and the similarity histogram of the choice set's schedules in figure 3) we have assumed the activity chain sequence dimension twice as important as the other two dimensions[4]. The computational effort for our $2514 \cdot 59 = 148,326$ schedule combinations was 2:01 min on a high-end Itanium single core computer, or about 0.8 ms per combination respectively.

5.6 Updating travel/activity times (step 3.2)

Based on the estimated utility function parameters, the Greater Zurich scenario may be rerun. The simulation results allow to update the travel times of both the chosen and non-chosen alternative schedules. Along with the travel times, the activity durations need to be adjusted, too.

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[4]Distance weight $\delta_{activity\_chain\_sequence} = 2 \cdot \delta_{mode\_choice} = 2 \cdot \delta_{location\_choice}$.

Table 3: Similarity histogram of the choice set's schedules.

# of occurrences in choice set
100% = 150,960
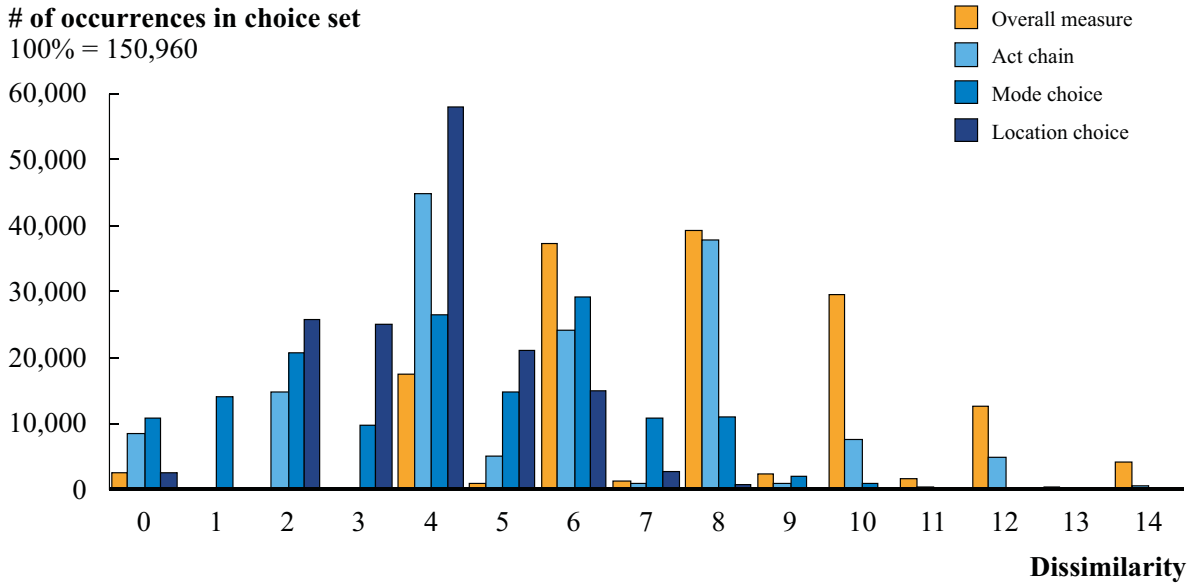
5.7   Estimation results (step 4)

At this point of time, we have focused on the estimation of the most relevant utility function parameters:

- the U_i^{max} parameters (U_{home}^{max}, U_{work}^{max}, $U_{education}^{max}$, $U_{shopping}^{max}$, $U_{leisure}^{max}$),

- the α_i parameters (α_{home}, α_{work}, $\alpha_{education}$, $\alpha_{shopping}$, $\alpha_{leisure}$),

- the $U_{travel,i}$ parameters ($U_{car,i}$, $U_{walk,i}$, $U_{bike,i}$, $U_{pt,i}$),

- the similarity parameter δ_{sim}.

All further parameters have been kept fixed at their initially (and arbitrarily) set values of table 1.

We have used Biogeme, version 1.8, to solve the MNL model (Bierlaire, 2003, 2009). Our first estimation results are both preliminary and ambiguous. Having adopted the above methodology, the loglikelihood function relaxes to a value of 0 ($\rho^2 = 1.00$) already in the first instance of step 3.1. This means 100% of the information in the sample is explained by the model. However, none of the parameters is significant (see table 4, left, and figure 4a).

This is very detrimental and we have ommitted, as a trial, the δ_{sim} parameter in a second estimation run neglecting the IIA property of the MNL model. Now, 13 out of the 14 parameters are significant. All parameters feature the expected algebraic sign. Their values are lower than

Table 4: First preliminary parameter estimates.

| Parameter	Estimation including Sim parameter			Estimation excluding Sim parameter		
	Value	t-test		Value	t-test	
Umax_home	59.9	0.29	*	4.1	34.62	
Umax_work	50.7	0.16	*	3.1	40.66	
Umax_education	39.4	0.31	*	1.9	21.10	
Umax_shopping	35.0	0.36	*	1.5	18.58	
Umax_leisure	13.8	0.00	*	2.3	33.17	
alpha_home	9.9	0.00	*	10.4	103.29	
alpha_work	5.4	0.19	*	3.8	39.10	
alpha_education	3.7	0.00	*	2.1	15.65	
alpha_shopping	1.9	0.00	*	0.1	0.00	*
alpha_leisure	3.0	0.08	*	0.5	6.01	
U_car	-6.3	0.00	*	-2.2	-24.68	
U_walk	-6.0	-0.01	*	-0.3	-7.96	
U_pt	-3.5	0.00	*	-1.0	-20.70	
delta_sim	-20.6	0.00	*	-	-	
Number of observations	2514			2514		
L(0)	-10,227.50			-9,761.94		
L(β)	-0.04			-5,884.18		
ρ2	1.00			0.40		

expected but the proportion among them seems reasonable. ρ^2 is 0.40. We have run two iterations of steps 3.1 and 3.2. Table 4, right, and figure 4b compare the second iteration's estimation results with the results of the run including the δ_{sim} parameter. Table 5 displays the development of the parameter values of the second run over the iterations. One can observe that the development is fairly flat and stable.

6   Summary and outlook

This paper proposed a new MATSim utility function for the performance of activities, based on an asymmetric S-shaped curve with an inflection point as presented by Joh (2004). The new function can cope with a flexible number of activities in an activity-travel schedule as it formulates an optimal activity duration by its functional form. The new function has become necessary since the algorithm *PlanomatX* has been added to MATSim's replanning step. *PlanomatX* comprehensively optimizes activity-travel schedules, including the activity chain sequences (Feil *et al.*, 2009).

This paper further presented a methodology to empirically estimate the parameters of the new utility function through an enhanced Multinomial Logit Approach (MNL). In order to over-

Figure 4: Illustration of the utility function for the performance of activities after preliminary parameter estimation.

(a) Estimation including Sim parameter.

(b) Estimation excluding Sim parameter.
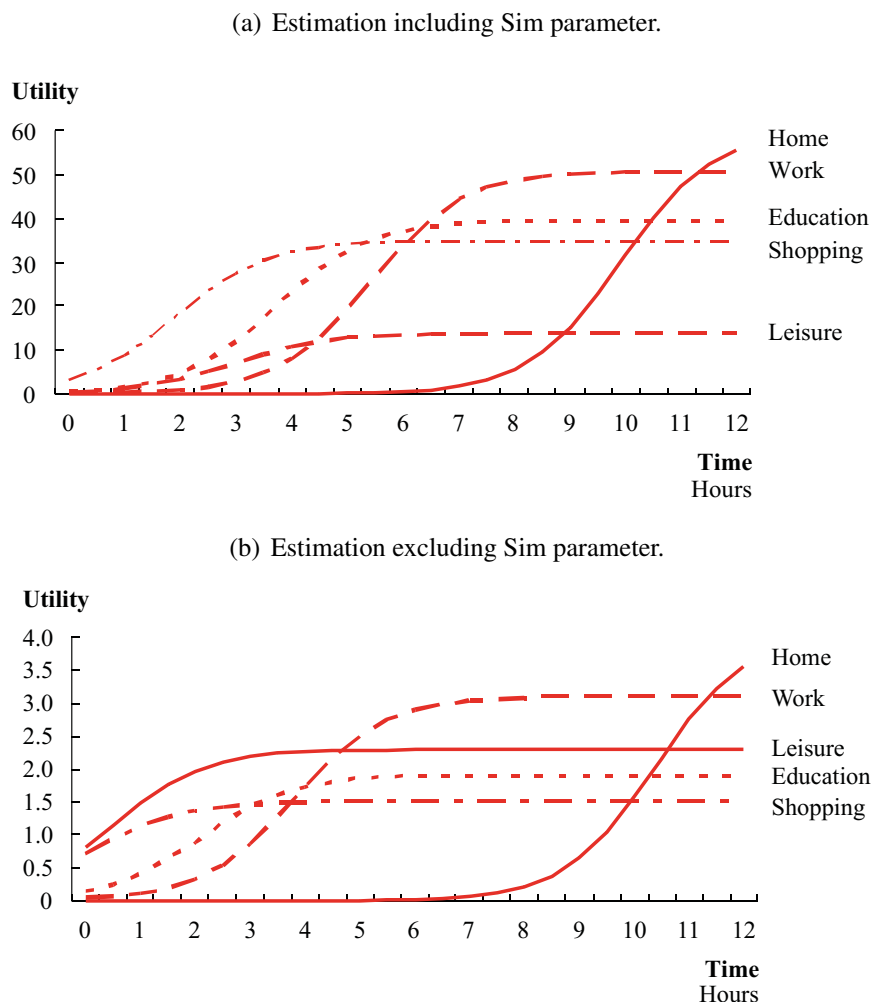
come the MNL model's IIA property a similarity attribute was added in the systematic part of the utility function. The attribute reflects the structural similarity between the schedules following the logic of the path-size logit or C-logit approach. It is calculated using a Multidimensional Sequence Alignment Method (Joh *et al.*, 2002; Joh, 2004) that, in our case, considers the similarity of two schedules along the activity chain sequence, mode choice, and location choice dimensions.

First estimates of a limited set of parameters have been conducted but the results are still unsatisfactory and ambiguous. A first estimate including the similarity attribute produced no significant parameter values, despite a maximum model explanation. A second estimate omitting the similarity attribute yielded mostly significant parameter values. Those values may though be biased by the MNL's IIA property.

Table 5: Development of parameter values over the estimation iterations excluding the $delta_{sim}$ attribute.

Parameter	0th iteration Value	0th iteration t-test		1st iteration Value	1st iteration t-test		2nd iteration Value	2nd iteration t-test	
Umax_home	4.4	34.02		4.0	34.11		4.1	34.62	
Umax_work	3.2	41.09		2.9	39.53		3.1	40.66	
Umax_education	1.9	21.22		1.8	20.11		1.9	21.10	
Umax_shopping	1.6	19.21		1.4	17.17		1.5	18.58	
Umax_leisure	2.3	33.61		2.2	32.65		2.3	33.17	
alpha_home	10.3	101.25		10.2	99.48		10.4	103.29	
alpha_work	3.9	39.53		3.7	37.26		3.8	39.10	
alpha_education	2.1	16.14		2.1	15.25		2.1	15.65	
alpha_shopping	0.0	0.00 *		0.0	0.00 *		0.1	0.00 *	
alpha_leisure	0.4	5.96		0.5	7.19		0.5	6.01	
U_car	-2.3	-24.81		-2.2	-24.59		-2.2	-24.68	
U_walk	-0.3	-7.94		-0.4	-8.04		-0.3	-7.96	
U_pt	-1.0	-20.72		-0.9	-20.56		-1.0	-20.70	
delta_sim	-	-		-	-		-	-	
Number of observations	2514			2514			2514		
L(0)	-9,770.43			-9,762.00			-9,761.94		
L(β)	-5875.44			-5931.6			-5,884.18		
ρ2	0.40			0.39			0.40		

Our next steps will concentrate on increasing the explanatory power of the estimation. This may require to refine the generation of the choice set (e.g., the location choice), include the utility function's β and γ parameters into the estimation, and/or test other utility function forms. We will also incorporate more attributes (e.g., monetary cost of travelling). A successful empirical estimation of the utility function parameters will finally set up MATSim's simulation results for an in-depth comparison with real traffic counts.

References

Balmer, M. (2007) Travel demand modeling for multi-agent traffic simulations: Algorithms and systems, Ph.D. Thesis, ETH Zurich, Zurich, May 2007.

Balmer, M., K. Meister, M. Rieser, K. Nagel and K. W. Axhausen (2008a) Agent-based simulation of travel demand: Structure and computational performance of MATSim-T, paper presented at *Innovations in Travel Modeling (ITM'08)*, Portland, June 2008, `http://www.trb-forecasting.org/innovationsConference2008.html`.

Balmer, M., K. Meister, M. Rieser, K. Nagel and K. W. Axhausen (2008b) Agent-based simulation of travel demand: Structure and computational performance of MATSim-T, *Working*

Paper, **504**, IVT, ETH Zurich, Zurich, June 2008, `http://www.ivt.ethz.ch/vpl/publications/reports/ab504.pdf`.

Ben-Akiva, M. E. and S. R. Lerman (1985) *Discrete Choice Analysis: Theory and Application to Travel Demand*, MIT Press, Cambridge.

Bierlaire, M. (2003) BIOGEME: A free package for the estimation of discrete choice models, paper presented at *the 3th Swiss Transport Research Conference*, Ascona, March 2003.

Bierlaire, M. (2009) *An introduction to BIOGEME (Version 1.8)*, `http://transp-or2.epfl.ch/biogeme/doc/tutorialv18.pdf`.

Charypar, D. and K. Nagel (2005) Generating complete all-day activity plans with genetic algorithms, *Transportation*, **32** (4) 369–397.

de Palma, A., N. Picard and P. Waddell (2007) Discrete choice models with capacity constraints: An empirical analysis of the housing market of the greater Paris region, **62** (2) 204–230.

Feil, M. (Forthcoming) Choosing the daily schedule: Expanding activity-based travel demand modelling, Ph.D. Thesis, ETH Zurich.

Feil, M., M. Balmer and K. W. Axhausen (2009) New approaches to generating comprehensive all-day activity-travel schedules, *Research Report*, IVT, IVT, ETH Zurich, Zurich, `http://www.ivt.ethz.ch/vpl/publications/reports/ab573.pdf`.

Horni, A., D. M. Scott, M. Balmer and K. W. Axhausen (2008) Location choice modeling for shopping and leisure activities with MATSim: Combining micro-simulation and time geography, paper presented at *the 8th Swiss Transport Research Conference*, Ascona, October 2008.

Illenberger, J., and K. Nagel (2007) Enhancing MATSim with capabilities of within-day re-planning, paper presented at *Intelligent Transportation Systems Conference (ITSC)*, Seattle, September 2007.

Joh, C.-H. (2004) Measuring and predicting adaptation in multidimensional activity-travel patterns, Ph.D. Thesis, Technical University Eindhoven, Eindhoven.

Joh, C.-H., T. A. Arentze, F. Hofman and H. J. P. Timmermans (2002) Activity pattern similarity: a multidimensional sequence alignment method, *Transportation Research Part B: Methodological*, **36**, 385–403.

Lefebvre, N. and M. Balmer (2007) Fast shortest path computation in time-dependent traffic networks, paper presented at *the 7th Swiss Transport Research Conference*, Ascona, September 2007, `http://www.strc.ch/conferences/2007/2007_lefebvre.pdf`.

McFadden, D. (1974) Conditional logit analysis of qualitative choice-behaviour, in P. Zarembka (ed.) *Frontiers in Econometrics*, 105–142, Academic Press, New York.

Meister, K., M. Rieser, F. Ciari, A. Horni, M. Balmer and K. W. Axhausen (2009) Anwendung eines agentenbasierten Modells der Verkehrsnachfrage auf die Schweiz, *Straßenverkehrstechnik*, **53** (5) 269–280.

Schüssler, N. and K. W. Axhausen (2007) Recent developments regarding similarities in transport modelling, paper presented at *the 7th Swiss Transport Research Conference*, Ascona, September 2007.

Vrtic, M. (2003) Simultanes Routen- und Verkehrsmittelwahlmodell, Ph.D. Thesis, Technical University Dresden, Dresden.