

Zoellig, Christof; Axhausen, Kay W

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Calculating benefits of infrastructural investment

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Calculating Benefits of an Infrastructural Investment

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Sustainable Regional Growth and Development in the Creative Knowledge Economy

Christof Zöllig

Institute of Transport Planning and Systems (IVT)
ETH Zürich (Hönggerberg)
CH-8093 Zürich

Telephone: +41-44-633 27 19

Fax: +41-44-633 10 57

christof.zoellig@ivt.baug.ethz.ch

Kay W. Axhausen

Institute of Transport Planning and Systems (IVT)
ETH Zürich (Hönggerberg)
CH-8093 Zürich

Telephone: +41-44-633 39 43

Fax: +41-44-633 10 57

axhausen@ivt.baug.ethz.ch

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Abstract

There is an ongoing discussion about how to measure the benefits of an infrastructural investment. It is argued that travel time savings disappear in the long run because of long term decisions such as location choice. This suggests to use more comprehensive utility indicators than travel time savings and to integrate long term decisions in transport models.

This paper illustrates that models with more degrees of freedom produce different results in terms of traffic distribution, volumes and consequently of utility gains. If long term decisions are considered, short term travel time savings do not capture utility gains appropriately. In this context we discuss the expected maximum utility as a comprehensive indicator, which has also the advantage of being highly consistent with discrete choice and welfare theory. The errors made when disregarding relevant dimensions are substantial and might influence the decision on whether to build a transportation infrastructure or not.

Key words

Random utility maximisation, travel time savings, expected maximum utility, micro-simulation, land use

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1 Introduction

To evaluate infrastructural projects it is common practice to perform a cost-benefit analysis *ex ante*. To assess the benefits of the investment, guidelines usually propose to predict travel time savings and to monetise them using values of travel time savings (e.g. VSS, 2006).

Travel time savings originate due to reduced traffic volume on congested links and higher speeds on better aligned links. To predict the expected reductions standard transport models usually allow for changes in route and mode choice as the relevant behavioural dimensions of travellers. However, it is pretty obvious that in reality travellers might also alter departure time or destination/location (if there are alternatives available) to adapt to a new transport infrastructure. Consequently, a model that does not consider departure time and destination/location choice might not include all consequences (processes) arising from an adapted transport infrastructure, especially in a long term perspective. A model that neglects relevant degrees of freedom, might produce misleading results in terms of calculated traffic volumes leading to misjudged utility gains. This issue was recently discussed in depth by Metz (2008).

The integration of other dimensions of decision making to calculate future traffic flows raises the question whether short term travel time savings are still an appropriate indicator to judge an infrastructural investment. When we assume that travellers do not only change their connections but also locations and departure time, we should integrate utility components influenced by such decisions into our models to maintain consistency. Therefore we want to show that it is relevant for evaluation whether we only consider travel time savings or more comprehensive utility indicators.

However, we do not discuss the question of what utility components to integrate in detail. The simplifying assumption is that the utility of an alternative can be calculated with the travel time on a given connection, the time of late or early arrival and the price of the activity at its location. Other aspects determining the utility of the traveller like comfort, risk or monetary costs are not considered for simplicity. We recognise that the integration of such aspects will be crucial for a fuller judgement but the focus of this paper is on the influence of additional decision dimensions.

This paper addresses the following research questions:

1. What differences in impacts of an improved transport system occur when we allow for more decision dimensions than route choice in the transport model?
2. Is it sufficient to calculate the benefits of an infrastructural investment in terms of travel time savings?
3. Would it be more consistent to evaluate an investment using the expected maximised utility¹ (EMU) from the underlying choice model?

Accordingly the research objectives are formulated:

1. Show that traditional models of transport assignment cannot show all effects of behavioural changes occurring after an infrastructural investment.
2. Investigate the difference in benefits in terms of travel time savings only and an approach considering utilities from departure time choice and location choice as well.
3. Compare the estimated utility gains derived by different indicators, namely travel time savings and the EMU.

To investigate these issues a proof of concept simulation is implemented using the programming language Python. The agent-based simulation approximates for a minimal urban system the stochastic user equilibrium of commuting inhabitants using discrete choice theory (Ben-Akiva and Lerman, 1985). The simulation of the agents' decisions results in traffic volumes on links and population densities at locations. The agent-based approach was chosen to respect the discrete nature, consistency with discrete choice theory and because it seems to be the way forward in the field (Zondag, 2007, 81).

The presented simulation allows us to study the differences in simulated data according to modelled behavioural dimensions. This will give us indications whether the dimensions of behaviour typically considered are sufficient to assess infrastructural investments. Here we have to point out that the model shall help us to make conclusions about modelling itself. We are interested in the degree of approximation. How far can we abstract behaviour in transport demand models if we want to estimate the benefits in a socio-economic system like a city?

To study this question we simulate the reaction of inhabitants to an infrastructural investment allowing for different degrees of freedom. Therefore the simulation contains three decision dimensions, which can be switched on or off. We then calculate demand and utility gains with different decision dimensions available. The experiments have to be designed in a way that

¹ See chapter 3.4.2 for explanation.

meaningful reactions with the applied choice spaces are possible. We analyse the results in respect of demand shifts and donated utilities.

We do not assume costs for the infrastructural investments because it is not necessary to calculate their profitability in terms of a cost-benefit ratio to answer the research questions. The costs are constant as long as the same investment is observed and will therefore not affect the results.

Primarily we do not want to uncover some real world phenomena for a real city. Therefore the simulation is abstract. Nevertheless the model may provide insight into the functioning of the system.

The paper is organised in four main sections. The first section explains the research method. The following section describes the implemented algorithm and the simulated experiments in detail. We show and interpret the results in section 4. The fifth section contains conclusions and an outlook.

2 Research Method

Robert Axelrod (1997) names simulation as third way of doing research combining induction and deduction. After making assumptions in deductive tradition we run the simulation to analyse the generated data inductively. Gilbert and Troitzsch (2005, p. 15) define simulation as follows:

“Simulation means 'running' the model forward through (simulated) time and watching what happens.”

The logic of simulation is very similar to statistical modelling. In statistical modelling we estimate parameters for a postulated model based on observed data. This quality is admirable if we have collected data at hand because it allows us to fit our model systematically to the observed data. The parameter estimates allow to make predictions afterwards.

In contrast, simulated (predicted) data is gained by simulation of a postulated model. Also the simulated data is compared to observed data if these are available. The better the similarity, the better the model. By building the simulation and comparing its output to observations we can check whether our assumptions about the functioning of the process are plausible or not. If we observe the expected behaviour we can assume our simulation to work correct. Simulation is especially useful if we want to study processes (Gilbert and Troitzsch, 2005).

In a very first step we might just want to check whether our idea of the process is plausible. In this stage we talk about a *proof-of-concept simulation*. In this stage it is possible to validate the simulations against expectations. This means that no explicit empirical data is needed. We just check whether the simulation is producing plausible output, based on what is known from experience and the literature.

The method of simulation can be used to gain more insight into a process or to make predictions. It is logical that the understanding of the process is the basis for predictions. This suggests that we should first build simulations to improve our understanding. In a second step simulations may be refined up to a level where useful predictions are possible. Simulations may be applied in practice after the second step.

We use an agent-based simulation to approach the research questions. Agent-based simulations represent a complex system by single components, which interact with each other. The components are named agents if they have an autonomous behaviour. We simulate the behaviour of the agents to reveal the system behaviour. This bottom up approach makes agent-based simulation an interesting tool for the analysis of complex systems.

Through interaction, phenomena emerge on the macro level. Emergence is either unforeseen or unpredictable (Gilbert and Terna, 2000). According to them unforeseen emergence is a phenomenon we just did not think of but would have been detectable by analysing the structure of the simulation in advance. In such a case the simulation helped us to think. Unpredictable emergence, on the other hand, is not detectable in advance.

3 An Agent-based Simulation

3.1 Description of the Simulation

We simulate the decisions of individual travellers to calculate the traffic flow on the transportation infrastructure. This is a disaggregate approach. Such models are based on the random utility theory pioneered by Daniel McFadden (1974). The economic framework was applied and detailed for the transportation context by Domencich and McFadden (1975). Ben-Akiva and Lerman (1985), Ortuzar and Willumsen (2001) and Train (2003) give comprehensive overviews and good introductions. The last book focuses especially on the use of the model framework in simulations.

Because we want departure time choice to matter, we aim for a congested network. Within congested networks the consideration of capacity restraints is important because link costs vary substantially according to the link load. Consequently, demand depends on the decisions of other individuals, which requires an iterative calculation. Therefore we solve the assignment problem numerically by simulating a series of random number experiments (Burrell, 1968).

The result of the assignment is a stochastic user equilibrium (SUE) because we include a randomly distributed utility component (see section 8). The user equilibrium is defined as the state of a capacity restraint transport system in which no traveller can find a better travel alternative any more. This is also known as Wardrop's equilibrium (Wardrop, 1952). In this state each traveller has optimised its personal situation, what we normally assume as the principle of best behaviour. In a more general economic system one would speak of a Walrasian equilibrium (Tsfatsion, 2006, p. 13).

The simulation at hand is on a performance level 1 according to the categorisation of Gilbert and Terna (2000). It is “in qualitative agreement with empirical macro-structure, as established by plotting the distributions of some attributes of the agent population.”

3.1.1 Model Components

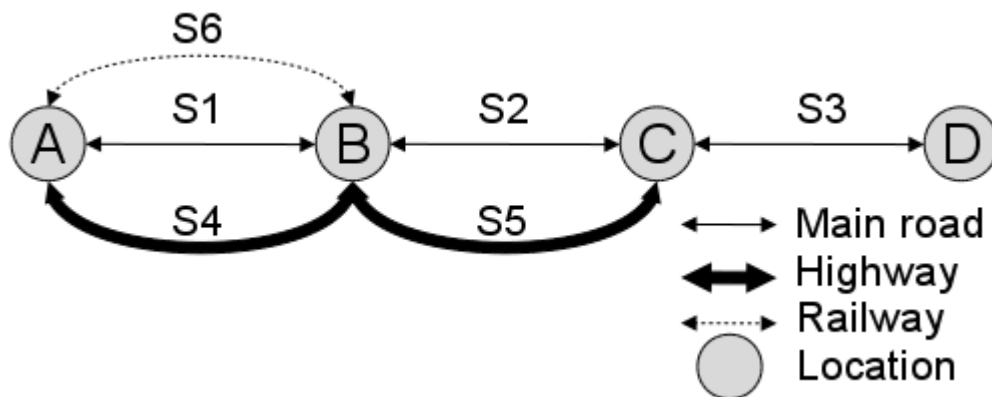
Locations

The simulation considers a minimal representation of a city. The city is represented by four locations A, B, C and D. A is the work location of all inhabitants. The houses where the agents live are located in B, C, or D. The locations have capacity to accommodate 600 agents each.

Transport Infrastructure

To get home from work the agents must make use of the transport infrastructure which consists of links connecting the locations. The links are either of type *main road* (S1, S2, S3), *highway* (S4, S5) or *railway* (S6). The number of links to peripheral locations is smaller because of the lower number of agents travelling so far (see figure 1).

Figure 1 Initial transport infrastructure of the simulation



To relate link load with travel time we apply capacity restraint functions. For the *main roads* and *highways* we use the BPR-function (Ortuzar and Willumsen, 2001, p. 325):

$$T_s = t_{0s} [1 + \alpha (V_s / Q_s)^\beta] \quad (3.1)$$

t_{0s} ...free flow travel time

V_s ...load on the link s

Q_s ...capacity of link s

α, β ...parameters specific to road type of link s

To consider the fact that a train can be full at a certain departure time we apply the function by Davidson (1966) for the *railway* link:

$$T_s = t_0 * [1 + \zeta * (V_s / Q_s - V_s)] \quad (3.2)$$

with ζ ... parameter specific for road type of link s

This approach neglects that travel time not only depends on the load of the link in question, but also on the loads of other elements in the network like subsequent or preceding nodes. The functions are characterised by a minimum travel time and a steady increase until the capacity is reached. The capacity defines the maximal throughput of a link. Note that link loads vary from time interval to time interval. The parameters specifying the capacity restraint functions are in the appendix (see table 8).

Agents

The city is populated by 1000 agents, all working in A and living in locations B to D. We assume a constant population and that all agents have to make a return-home trip.

The agents want to optimise their utility by choosing from the choice set the alternative with maximum utility. The objective function of the agents is:

$$\max (U) = \max(V(X) + \varepsilon_{rtj}) \quad (3.3)$$

The stochastic utility U is the sum of the deterministic utility given by a utility function and a random utility. We assume the random utility components to be independently and identically Gumbel distributed. Accordingly we apply a multinomial logit model (MNL).

In this simulation the random part ε_{rtj} of utility is generated once per agent and specific alternative. The random part represents the unknown preferences of the agent. This random preference for an alternative remains constant during the simulation (see also section 3.2).

The deterministic utility is an additive, linear combination of weighted utility components. The utility components are a function of the three choices *connection choice* (r), *departure time choice* (t) and *destination choice* (j).

$$V(r, t, j) = \beta_r * V_r(r, t, j) + \beta_t * V_t(r, t, j) + \beta_j * V_j(j) \quad (3.4)$$

with $\beta_r, \beta_t, \beta_j \dots$ weight parameters

The explanatory variables are options at the corresponding decision dimension. The options at each decision dimension can be described as sets.

We model mode choice in a simplified way by presenting *connections* as alternatives. We define *connections* as a sequence of links from origin to destination of a trip. For the link sequence it does not matter whether the link is assigned to public transport or individual transport. This means that an agent is allowed to continue his trip on a road even though he travelled on a rail way link before. The set of connections consists of all possible sequences of links from location A to one of the locations B, C or D. These locations are the options for destination choice. The initial network provides 15 connections.

Time is represented as a set of 24 possible departure time intervals. Each interval represents 5 minutes which qualifies the model as *dynamic* (Janson, 1991, p. 143). This means that the agents have a time span of 2 hours to leave from work. Note that in the simulation time is represented as a discrete quantity.

Each combination of the options makes up an alternative of the choice set. Not all combinations are actually valid alternatives. It is for example meaningless to choose a connection, which does not correspond to the selected location. With other words we just consider possible alternatives in the choice set.

Travel time utility has the following functional form:

$$V_r(r, t, j) = \beta_g * T_r \quad (3.5)$$

with $T_r = \sum_s T_s * \delta_s^r$ ($\delta_s^r = 0$, if s is part of connection r ; $\delta_s^r = 1$, otherwise)

The formula shows that travel time utility depends on connection choice, departure time choice, location choice and an agent specific value of travel time savings (VTTS) β_g . We just distinguish between agents which have a high VTTS ($\beta_g = -2$) versus agents with a low VTTS ($\beta_g = -1$). T_r is the sum over the link travel times T_s which are part of the connection. Travel time T_s is calculated with the capacity restraint function corresponding to link s .

To model the utility originating in punctuality we use a formulation following Small (1982). Small introduces the arrival time $\tau = t + T_s$ and calculates than the utility according to:

$$V_t(\tau) = \zeta * SDE(\tau) + (\gamma * SDL(\tau) + \delta * d_L) \quad (3.6)$$

with $SDE = \max(PAT - \tau, 0)$

$SDL = \max(\tau - PAT, 0)$

$d_L = 1$, if $\tau > PAT$, $d_L = 0$, if $\tau \leq 0$

PAT ... preferred arrival time

δ ... penalty for being late

ζ, γ ... utility loss rates for SDE and SDL respectively

The utility depends on the difference between arrival time τ and the preferred arrival time (PAT) which is set to the beginning of time interval 24. Utility from punctuality depends on choices in all three dimensions because arrival time depends on travel time.

Utility from location choice is calculated with the following function:

$$V(j) = \exp(\lambda * A_j / Q_j) \quad (3.7)$$

We follow the common assumption about prices of limited goods responding to demand. In a very rough approximation we assume that living costs at location j depend on the availability of living space, which is represented by the occupancy rate. The occupancy rate is the coefficient of capacity Q_j of location j and the number of agents A_j selecting location j . The parameter λ allows to make the simulation more sensitive with respect to occupancy rates of locations.

For destination choice non-linear functions have been found more appropriate (Foerster, 1981; Daly, 1982). Therefore we assume that costs increase exponentially with the occupancy rate.

The utility functions are actually rather cost functions. Utility gains are visible in reduction of costs. We should keep this in mind for the interpretation of the results.

It is obvious that we are not claiming to integrate all important costs. We would have to model house costs, costs of mobility tools (fix costs of vehicles, season tickets etc.), transfer costs and so on.

3.2 Experiments

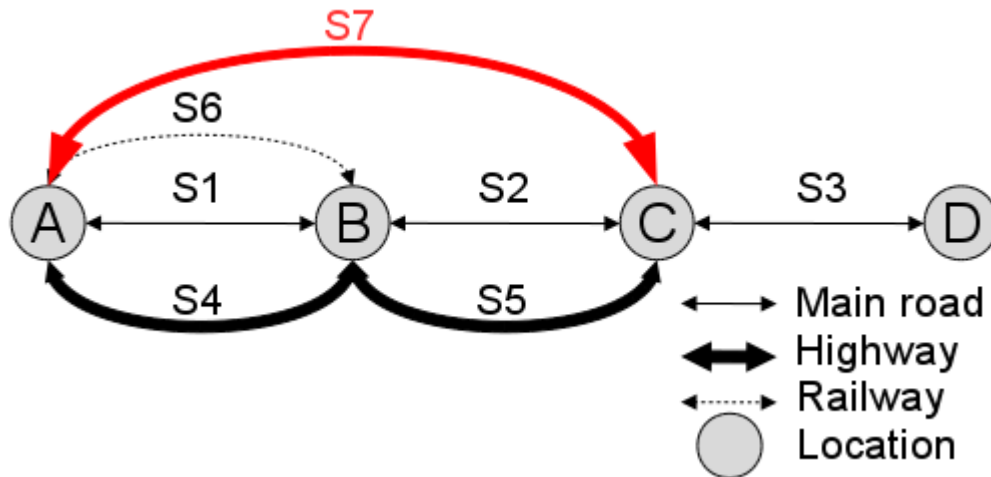
We simulate the reaction to an infrastructural investment. The experiment consists of calculating a SUE for the initial conditions (state 1), introducing an infrastructural investment and calculating four subsequent SUE as a reaction to the investment (states 2) with different degrees of freedom for the agents. Note that subsequent SUE depend on the degrees of freedom (available decision dimensions) and the infrastructural investment. The random components of the alternatives' utilities are generated once per experiment.

3.2.1 Infrastructural Investment

We experimented with three types of investments. We introduced new links, modified existing links or deleted links. For the two first types we tested several variations.

In this paper we just discuss the results of one scenario. A new highway S7 shall connect the working location A directly with peripheral location C. The link has a free-flow travel time of 5.0, a capacity of 40 agents per time interval and is characterised by a BPR-function.

Figure 2 Transport Infrastructure of the simulation with the New Highway S7



The investment leads to a new choice set. The choices of the agents will change if the new alternatives promise better utility. The new decisions will lead to a new equilibrium.

The agents also have a preference for new alternatives. Therefore we have to generate a new stochastic component for each agent and new alternative. We further assume that the preferences towards the old alternatives stay the same.

3.2.2 Choice Spaces

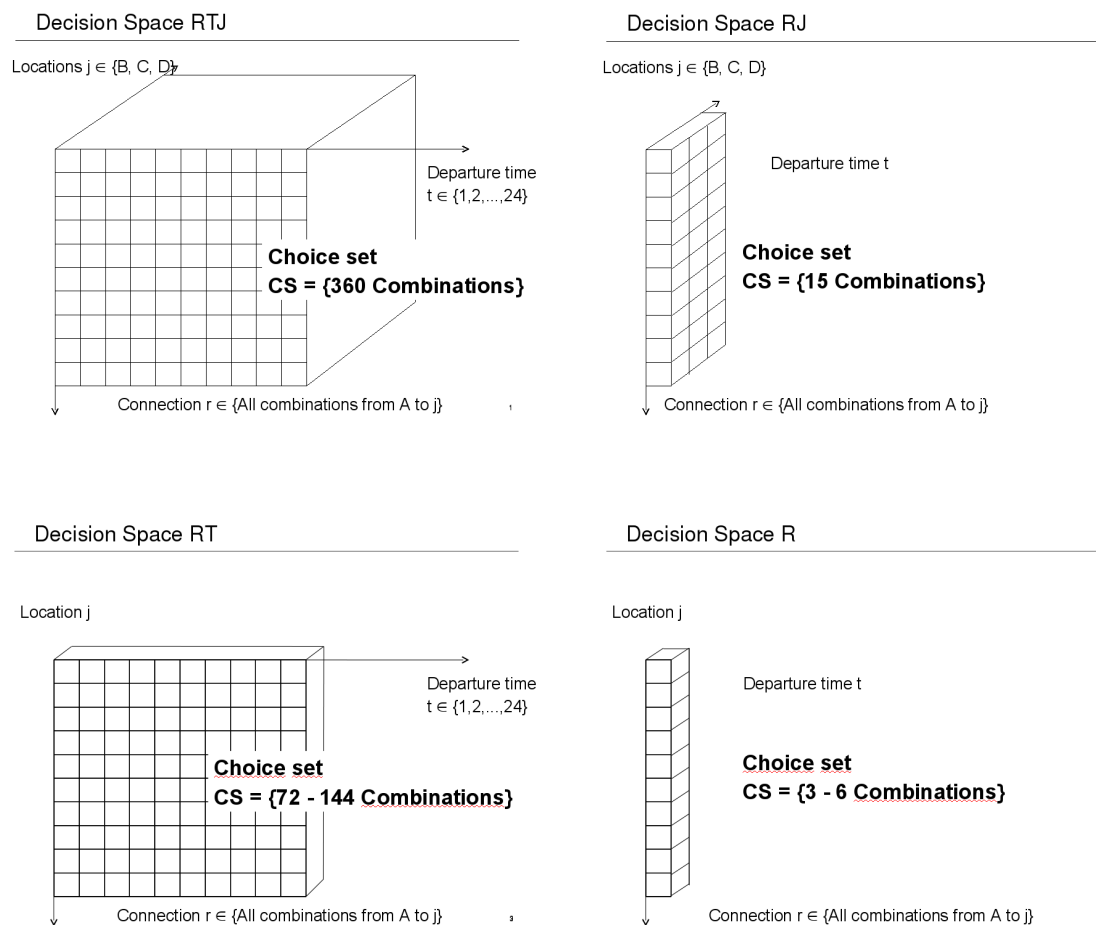
The combination of decision dimensions we name *choice spaces*. We experiment with four choice spaces:

- RTJ
- RT
- R
- RJ

Each letter represents a decision dimension for which the agents have a discrete number of options. If a dimension is not present, all agents will retain their option chosen earlier at this dimension. This means for example that the agents' departure time cannot change in choice space RJ. As a consequence the number of alternatives is very different according to applied choice space (see figure 3).

We note that restricted choice spaces depend on the decisions made earlier by the agents. Therefore we have different numbers of possible combinations for choice spaces RT and R. This means that restricted choice spaces are individual. The number of utility components of overall utility remains the same for all choice spaces.

Figure 3 Visualisation of Choice Spaces



The choice spaces in figure 3 reflect the initial transport infrastructure. If we consider the network with S7, we have 408, 17, 72 up to 168, 3 up to 7 combinations for choice spaces RTJ, RJ, RT and R respectively.

The EMU considers only available alternatives by definition (see formula 3.8). This means that the EMU is sensitive to the choice space. Let us take choice space RT as an example. We

do not consider alternatives with a location different from the currently selected for the calculation of the EMU. Therefore the choice set is smaller and consequently the EMU. To isolate the effect of the infrastructural investment from the effect of more degrees of freedom we calculate the EMU before and after the investment with the same choice space.

We require that connection choice and location choice are consistent. This has implication for the number of possible choice spaces. It is not possible to choose a new location without choosing a new connection as well. Therefore the combinations TJ and J are not considered.

The choice space has also to be appropriate for the investment, meaning that the agents should be able to react to the investment. For example, agents with a choice space T cannot react to a new link, because they cannot chose a new connection. If we had an investment spreading PAT of the agents, choice space T would make more sense. This also means that the differences between the results simulated with different choice spaces depends on the investment studied.

3.2.1 Calculation of SUE

Algorithms formulated to solve aggregate models (Fernandez and Friesz, 1983) are not applicable in a straight forward way because of the discrete nature of agent-based models. Unlike flows agents cannot be split. Hence, an infinitesimal approximation of the equilibrium is not possible. To meet theoretical equilibrium conditions is unlikely because the approximation of equilibrium conditions is only possible up to the “agent resolution”.

To find the SUE of state 1 and state 2 an iterative incremental assignment algorithm is implemented:

1. Load the initial conditions and set the number of iterations $n = 0$.
2. Calculate the number of choosing agents $M = \text{number of agents}/(n + 1)^2$.
3. Order the agents by descending maximal potential utility gain.
4. Select the first M agents.
5. Randomise the order of these M agents.
6. Let these agents make their decisions one after the other and update the network after each decision.
7. Update the utilities of all agents for the chosen and non chosen alternatives.
8. Calculate the maximal potential utility gain and other attributes for each agent.
9. Calculate statistics of the whole system.
10. Go back to step 2 as long as $n < 20$ or sum of potential utility gains \neq minimum of potential utility gains in all preceding iterations. Also stop iterating if no agent

finds a better alternative, oscillation occurs or the maximum number of iterations is reached.

Reasons for the formulation of the algorithm

The updating of the network after each decision is the extreme case of an incremental assignment. Extreme situations in which many agents choose the same alternative are avoided. This leads to a pretty good approximation already in the first iteration.

A drawback of the incremental assignment is the information bias which handicaps agents deciding early. The first agent choosing does not know anything about later decisions until the utilities of the alternatives are updated at the end of an iteration. Therefore the agent might end up with a non-optimal alternative. By iterating several times over the population we overcome this problem.

To speed up equilibrium search we calculate the maximum potential utility gain for each agent considering the current utilities at the end of each iteration. Then we let these agents re-decide which have the highest potential utility gain.

The termination condition is rather complex because of possible oscillation and unsteady convergence respectively. Because of oscillation we cannot rely on the theoretical termination condition of no agent switching the selected alternative. Let us think of a single remaining agent to decide, which will choose the alternative with highest utility. This leads to a decrease of utility of this specific alternative because the loads are now higher. Possibly the previous alternative with new loads is again better for the agent and therefore switches back. This mechanism leads to oscillation.

One could argue that the agent choosing shall consider the effect of having chosen the alternative before. To find the actually best alternative in an iteration the agent would have to compare the before chosen alternative minus its demand for all other alternatives plus its demand. In each case new network loads would have to be calculated. Already in this small system storage requirements and computation time would increase substantially which makes accepting one oscillation cycle the better option.

The unsteady convergence obliges us to set a minimum number of iterations. To be sure to stop iterating with a good approximation of the equilibrium we require that the average

relative potential utility gain, an indicator for how close we are to the equilibrium, is equal to the minimum calculated value of this quantity during the iterations before.

Still this means that the algorithm cannot guarantee to find the exact equilibrium. If we hit a local minimum in the preceding iterations the algorithm will stop too early.

We define the reduction of agents deciding such that after the minimum number of iterations approximately 1% of all agents decide again. The minimum number of one agent choosing is reached after 22 iterations. The maximum is set as $n = 40$.

3.3 Parametrisation

Because the simulation is very abstract and not based on empirical data, we assume the parameters such that the average elasticity of demand y_a of alternative a with respect to travel time is approximately 0.6. Further we required that the elasticities of demand in respect to the utility components have the following relation: $E(y_a, V_r) > E(y_a, V_t) \gg E(y_a, V_j)$. The idea behind this requirements is that it is easy to change connection, hard to change departure time because of fixed working hours² and even harder to change location. Table 1 shows that the requirement is met in this simulations.

Table 1 Statistics of the Alternatives' Elasticities of Demand in Respect to Utility Components

Averages of 15 Simulations	V_r Connection	V_t Departure Time	V_j Location
Mean elasticity	0.499	0.100	0.032
Coefficient of variation	0.004	0.005	0.013

Furthermore we require that the agents are distributed over all links and locations. The distribution over all links ensures that the fastest links are congested in some time intervals and that changing to an earlier or later time slot is not a better alternative because of late or

² One could argue that departure time is easiest to alter. This is only true for people which determine their schedule themselves. Employed people, however, have an externally determined schedule which they cannot change that easily.

early arrival. Therefore utility loss of early or late arrival must be chosen high enough to make agents changing the link. This ensures that the agents make trade-offs between all decision dimensions. Further additional travel time shall be punished harder than earlier arrival. The parameters of the utility function and the capacity restraint functions are set accordingly. They are shown in table 10.

3.4 Indicators of Utility Gain

To evaluate infrastructural investments various assessment schemes have been developed. They have in common that they suggest one or more indicators upon which decisions are taken. Usually these indicators are calculated on the basis of traffic volumes predicted using a transport model.

The projects have to be judged from a social point of view. The assessment has to answer the question whether the project increases welfare for society. Costs and benefits for society are compared. The benefits are the reductions in *generalised costs* due to a certain investment. Within cost-benefit analysis discrete choice models provide a new indicator, the *expected maximum utility* (EMU). A comprehensive literature review and explanation can be found in De Jong (2005).

3.4.1 Generalised costs

In the most general sense generalised costs are calculated by summing up the resource consumption which arises for society given a certain development path. A path producing less generalised costs is preferable, at least from an economic point of view.

Applying this concept in a discrete choice model means to sum up all costs (or utilities) of the chosen alternatives given a certain transport supply. We will name this quantity $\sum Realised\ utility$ because the utility has actually been experienced by the traveller using an alternative. An improvement of the situation is achieved when the sum of all costs is reduced.

Some of the costs depend more obviously on transport infrastructure than others. Usually the focus is the cost of a trip: travel time costs, ticket costs, costs occurring due to unpunctuality or discomfort. More precisely we could speak of *perceived travel costs*. Already less obvious are the costs of season tickets, car ownership or even taxes which are paid to build transport

infrastructures. Such costs may be spoken of as *unperceived travel costs*. The third type of costs arise indirectly. They are *external costs* or *secondary costs*, such as emission costs, opportunity costs, or costs of accidents.

We note that not perceived and secondary costs are long run costs. This means that they become relevant in a long term perspective which we are dealing with when judging an infrastructural investment.

3.4.2 Expected Maximum Utility (EMU)

In contrast to realised utility the EMU considers the utilities of all alternatives in the choice set of each traveller n . The formula for the EMU (Ben-Akiva and Lerman, 1985) of a traveller n is:

$$EMU_n = 1/\alpha_n * \ln(\sum_A e^{V_{na}}) \quad (3.8)$$

with A ... choice set of traveller n

α_n ... marginal utility in income of traveller n (here set to 1.0)

An important property of the EMU is that it grows steadily with the addition of new alternatives. This means that the indicator depends on the number of alternatives in the choice set. The logarithmic formulation is chosen to account for the law of decreasing marginal utility.

The EMU describes the potentially available utility of an individual. The individual cannot make use of all this utility because it can just select one alternative. The EMU is therefore a potential.

In the economic welfare analysis we assume that welfare depends on the individual's possibilities in its life situation. Thus we can interpret the EMU as a welfare indicator (McFadden, 1981). An individual which has access to more possibilities is supposed to be better off. In transport research the same formula is interpreted as accessibility (Ben-Akiva and Lerman, 1985).

If we want to calculate the increase in welfare of a whole population due to infrastructural investment, we simply compute the difference between the sums of all agents' EMU before and after the intervention.

4 Results

In this section we present the differences between simulation results calculated with choice spaces RTJ, RT, R and RJ respectively. All the results refer to the scenario with the newly introduced highway S7. To have an idea of the robustness of the results we simulated the scenarios 5 times each. The result tables usually contain the average of 5 simulations. The coefficients of variation in the appendix (table 12 to 17) show the variance of the results.

The difference in an indicator I between state 1 and state 2 are the predicted changes due to the investment. These are computed as follows for each choice space X:

$$\Delta X = I_{2X} - I_1 \quad (4.1)$$

The simulation with RTJ is the benchmark as it provides all options. Therefore we compare predictions with choice space RTJ to predictions which neglect decision dimensions. The absolute error made with a choice space X is given by:

$$F_X = \Delta X - \Delta RTJ \quad (4.2)$$

The relative error is given by:

$$f_X = F_X / \Delta RTJ \quad (4.3)$$

The simulated data are compared on the basis of:

- link and locations loads
- total travel time ($\sum Travel\ time$)
- total travelled distance ($\sum Travelled\ distance$)
- total of realised utility ($\sum Realised\ utility$)
- total of utility potentials ($\sum EMU$)
- external costs

We focus on indicators which are describing the population in this section. To calculate the indicator for the whole population we sum up the indicators of the individual agents. We mark that with the sigma sign.

We start out with describing the simulated equilibria by means of link and locations loads. We then show the indicators of total travel time and total travelled distance. We proceed with presenting the calculated utilities, utility gains and external costs. In section 30 we describe the accuracy of calculated equilibria.

4.1.1 Quantity Indicators

The simulated loads of locations and links depend on the choice space used for simulation. We show this in table 2 and figure 4. Table 2 shows different occupancy rates of agents residing in B, C or D according to choice space applied.

If location and departure time choice is possible, the agents react by exploiting the higher accessibility of location C and D. We note higher total occupancy of location D (increase of 3%) while occupancy at location B is lowered (4%). Surprisingly, the total occupancy in C remains the same. For explanation we have to have a closer look at the occupancy rates of agents with high and low time value respectively.

We see that the occupancy of agents with a high value of travel time increases in C by 6% while the occupancy of agents with a low one decreases by 5%. It is interesting to see this process of agents with low time value being crowded out from location C to location D. Looking at the values at location B we recognise that some agents with low time value take the opportunity to reside nearer to working location A (increase of 2%).

In a way we are also capturing a social process which is forming the environment we live in. The process of gathering agents with similar characteristics can be interpreted as self selection which forms social segregation. From this point of view the simulation shows a segregation phenomenon first simulated by Schelling with his famous segregation model (Schelling, 1969). The different shares of agents with different characteristics (in this case just low or high time value) points at the influence of transport infrastructures on the social structure at locations.

If agents can adapt connection and location only, the occupancies show a higher movement of agents with low time value to peripheral locations. The explanation is that agents choose their

location such that they arrive punctually. They search for lower living costs and low costs because of unpunctuality. This way they actually benefit from travelling an equal duration but faster.

Obviously, simulations which neglect location choice will not predict occupancy rates different from state 1.

The rates in table 2 can also be interpreted as living costs at the corresponding locations. Therefore we can argue that simulations with location choice predict price variations at locations. In this case such models suggest that owners of living space in location D have benefits while owners of living space in location B have losses.

Table 2 Occupancy Rate of Locations by Choice Spaces and Time Values of Agents

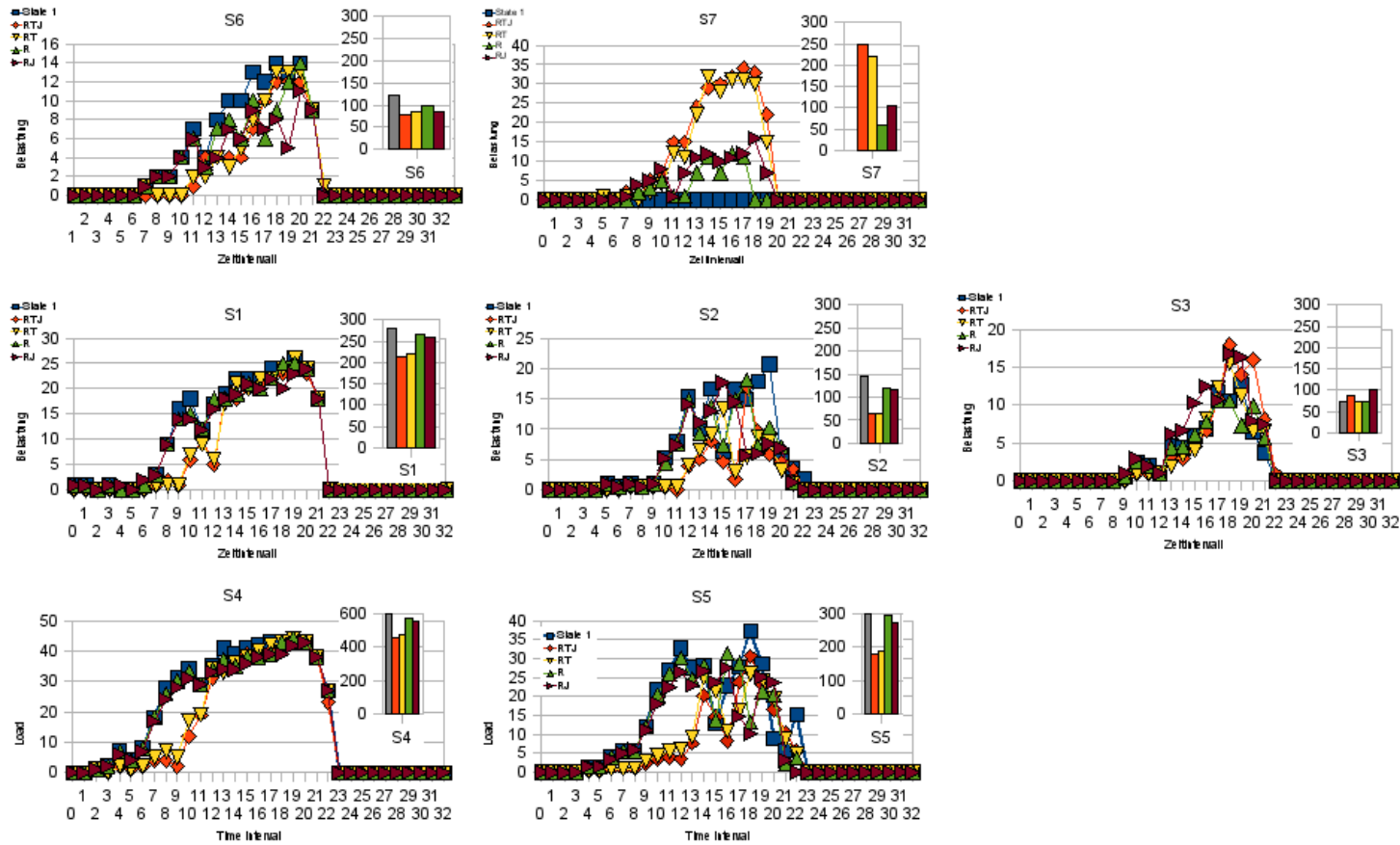
Average of 5 Simulations [%]	B			C			D		
	Total	High	Low	Total	High	Low	Total	High	Low
State 1	88	82	6	67	3	64	12	0	12
RTJ	84	76	8	67	9	59	15	0	15
RT	88	82	6	67	3	64	12	0	12
R	88	82	6	67	3	64	12	0	12
RJ	84	79	5	66	6	6	16	0	16

Figure 4 shows that also the loads of links are different depending on choice space used. Clearly, the different loads will influence the utility of the alternatives and therefore produce different equilibrium states for the whole system.

In the link loads we observe as well the consequences of neglected location choice. More obvious, however, are the differences which arise due to departure time choice. With choice spaces RTJ and RT agents will depart later which is visible in the graphs of S1, S4 and S6.

The graph of S7 shows that with restricted departure time choice the number of predicted agents choosing the new link is smaller compared to simulations with departure time choice. The reason is that the departure times of the agents are given. The given departure times of the agents disperse travel demand on the time axis. Hence, it needs only a few agents changing connection to resolve congestion in the preferred time slots.

Figure 4 Link Loads



In table 3 we see that the total of travel time decreases with all choice spaces as expected. However, we note that the decrease is not the same for all choice spaces. It is plausible that choice space RT reveals a high reduction in travel time. Only with the possibility to change departure time the agents are able to profit fully from the investment as shown above. In case of choice space RJ the high travel time saving origins in the given distribution of departure times. When all three dimensions are available the travel time savings are not as high because more agents chose peripheral locations.

Travelled distances increase with location choice. The agents make use of the increased accessibility of location D where they can profit from low living costs (see table 2). This is reasonable. That $\sum \text{Travelled distance}$ does not change with connection choice is an artefact of the equal distances assumed for the links.

Table 3 Predicted Changes by Choice Space

Average of 5 Simulations	ΔRTJ	ΔRT	ΔR	ΔRJ
$\sum \text{Travel time [min]}$	-1187	-1647	-1505	-1665
$\sum \text{Travelled distance [km]}$	874	0	0	1086

Table 4 contains the absolute and relative error of predicted changes in travel time and travelled distance. The errors are generally very high. In respect of travel time savings we do overestimate the gains when decision dimensions are neglected.

The prediction of travel time reduction is overestimated up to 43%, if we neglect departure time choice. Neglecting departure time choice and location choice leads in this case to an overestimation of 30% and neglecting location choice of 41% respectively. This finding is consistent with the notion that travel time savings tend to disappear in a long term perspective in which location choice should be considered as well.

Without location choice no variation in travelled distance can occur. That is why the change of travelled distance is underestimated by 100% with such choice spaces. Neglecting departure time choice leads to an overestimation of 24%.

Table 4 Absolute and Relative Error of Predicted Change by Choice Space

Average of 5 simulations	F_{RT}	f_{RT}	F_R	f_R	F_{RJ}	f_{RJ}
Σ Travel time	-460	0.41	-318	0.30	-478	0.43
Σ Travelled distance	-874	-1.00	-874	-1.00	211.6	0.24

4.1.2 Utilities

Table 5 shows the predicted changes in the utility indicators: ΣEMU and $\Sigma Realised utility$. The deltas of both over all indicators have a positive sign with any choice space. This shows the expected increases in utility because of the investment. ΣEMU and $\Sigma Realised utility$ show different utility levels. This is not very surprising because they measure different things.

$\Sigma Realised utility$ shows the expected increase in utility gains with additional decision dimensions. This demonstrates that neglecting decision dimensions leads to underestimation of utility gains. The reason is that agents cannot profit from all possible utility gains with reduced decision dimensions. We see this by analysing the composition of the realised utility. The three utility shares ΣV_r , ΣV_i and ΣV_j show us the composition of $\Sigma Realised utility$. The results show that the compositions are quite different. This means that the agents gain their utility differently according to the choice space. More decision dimensions provide the agent with more possibilities to adapt to new circumstances. The agents can make better use of the available alternatives. However, we cannot allocate utility gained through an additional decision dimension to one utility component because a choice at one dimension influences all components.

ΣV_r is the utility share arising from travel time savings. This indicator is not showing the same utility gains as the more comprehensive indicators of $\Sigma Realised utility$ and ΣEMU . Further we see that the indicator is not showing the same utility gains with respect to choice spaces. Neither do we find the expected increase in utility with more degrees of freedom. Contrasting the utility of travel time savings with the realised utility shows that the utility is not lost but transferred to other utility components. This demonstrates that travel time savings do not capture all utility gains. We conclude that utility gains from travel time savings do not

capture all utility gains if decision dimensions such as departure time choice and location choice exist.

Table 5 Predicted Utility Change by Choice Space

Average of 5 simulations	ΔRTJ	ΔRT	ΔR	ΔRJ
$\sum EMU$	302.91	166.95	158.95	437.70
$\sum V_r$	68.79	111.50	102.74	129.83
$\sum V_t$	73.76	53.02	-15.31	-27.87
$\sum V_j$	133.34	0.00	0.00	157.82
$\sum Realised\ utility$	275.88	164.52	87.43	259.78

As mentioned before we assume that the prediction with choice space RTJ is most accurate. In table 6 we list the errors in predicted utility gains compared to the prediction made with choice space RTJ. We note substantial errors. For over all utility indicators we generally see underestimation. This up to 68% for the indicator $\sum Realised\ utility$ with choice space R. In case of choice space RJ $\sum EMU$ overestimates the utility increase by 44%. This is due to the given “regime” of departure times as discussed above.

The components of the realised utility show even higher errors which reflects the suppressed trade-offs. Utility out of travel time savings is generally overestimated. The relative errors are very high with 65%, 54% and 95% respectively.

The utility component of punctuality $\sum V_t$ is underestimated in all restricted choice spaces. This shows that all three decision dimensions need to be available to get maximum utility out of punctuality. The error is obviously smaller if departure time choice is available (only 28%).

Utility gains because of relocation are underestimated by 100% if location choice is absent. If the agents cannot adjust their departure time, utility from location choice is still overestimated by 18%.

Table 6 Absolute and Relative Error of Predicted Utility Change by Choice Space

Average of 5 simulations	F_{RT}	f_{RT}	F_R	f_R	F_{RJ}	f_{RJ}
ΣEMU	-135.98	-0.45	-143.96	-0.47	134.79	0.44
ΣV_r	42.72	0.65	33.95	0.54	61.05	0.95
ΣV_t	-20.74	-0.28	-89.07	-1.21	-101.63	-1.38
ΣV_j	-133.34	-1.00	-133.34	-1.00	24.48	0.18
Σ Realised utility	-111.36	-0.40	-188.46	-0.68	-16.10	-0.06

We expect that the presented errors are quite high because the evaluated infrastructural investments alter the system substantially with respect to its size. In real world networks the errors might be smaller.

4.1.3 External Costs

It is clear that estimated external costs also depend on the choice space simulated given that omitting decision dimensions leads to different network loads (chapter 4.1.1). In table 7 we list the changes in predicted annual external costs calculated with the simplified approach of the Swiss Standard SN 641 828 (VSS, 2006).

The changes in accidents cost dominate. The accident costs decrease compared to the reference state because there is more traffic on highways. Highways have an accident cost rate per vehicle kilometre which is approximately ten times smaller compared to main roads. All other external costs rise because total travelled distance by car increases. The reasons are choice of peripheral locations and reduced usage of railway.

Table 7 Changes in Predicted External Costs

Average of 5 simulations [CHF / a]	ΔRTJ	ΔRT	ΔR	ΔRJ
Accident costs	-479'103	-472'676	-154'474	-148'352
Traffic noise costs	9'849	4'584	2'421	9'990
Air pollution costs	26'462	13'633	7'201	25'501
Climate costs	5'706	2'655	1'403	5'787
Sum external costs	-437'087	-451'805	-143'449	-107'074

Table 8 shows the absolute and relative error of estimated external costs in respect of the estimations with choice space RTJ. The relative errors have absolute values within a range of 21 – 77%, which is substantial.

If we do not model location choice we underestimate the increase in costs of traffic noise, air pollution and climate change. Without location choice we do not consider the increase in total travelled distance.

In case of simulating connection and location choice we overestimate the number of agents travelling longer distances (see chapter 4.1.1). The result is overestimated external costs.

Neglecting departure time choice results in high underestimation of accident costs. The reason is the lower usage of the new highway S7 (see figure 4).

Table 8 Absolute and Relative Error of Estimated External Costs by Choice Space

Average of 5 simulations	F_{RT} [CHF / a]	F_{RT} []	F_R [CHF / a]	F_R []	F_{RJ} [CHF / a]	F_{RJ} []
Accident costs	6427	-0.01	324630	-0.67	330751	-0.69
Traffic noise costs	-5265	-0.54	-2163	-0.21	7569	0.77
Air pollution costs	-12829	-0.49	-6432	-0.24	18300	0.69
Climate costs	-3050	-0.54	-1253	-0.21	4385	0.77
Sum external costs	-14718	0.04	308356	-0.71	36375	-0.09

4.1.4 Approximation of Equilibrium

Several variations of the algorithm were tested. They vary the point in time of network updates, the function to reduce the number of choosing agents, the criteria to stop the simulation and the minimal number of agents remaining to choose. None of the algorithm's variations is able to ensure reaching the SUE in which potential utility gains in the next iteration would be 0.

Because convergence to the SUE is not reliable, we stop iterating when the best solution out of at least 20 iterations is equalised or exceeded. To see how close the solution is to the SUE, we compute the average relative potential utility gain per agent. This indicator shows that the agents find very good alternatives. In general an average improvement of no more than 2.1% is still possible (see table 9). We reason that this is an acceptable approximation given the coarse resolution (3 locations, 1000 agents).

We note that the calculated equilibria are less accurate with more decision dimensions. With more degrees of freedom it is harder to find the optimal solution. The coefficients of variation, on the other hand, show that simulations with more degrees of freedom produce more stable results in terms of accuracy.

Table 9 Statistics for the average potential utility gain per agent

Statistic ³	RTJ	RT	R	RJ
Average [%]	2.0	1.5	0.4	0.3
Maximum [%]	2.1	1.7	0.6	0.5
Coefficient of variation	0.045	0.119	0.541	0.410

³ The statistics are calculated on the basis of 5 simulations.

5 Conclusions

The simulation experiments let us conclude that neglecting decision dimensions in a transport model overlooks important effects occurring after an infrastructural investment. In this paper we show that traffic flows in the transport system vary according to choice space. Consequently utilities calculated depend as well on the number of decision dimensions considered. This concerns also the utility component of travel time savings. The results indicate that the utility from travel time savings is overestimated, if departure time and/or location choice are not considered. Different compositions of the realised utility suggest that the reason lies within trade-offs between utility components. With more decision dimensions more trade-offs are possible.

A lot depends on the decision situation considered. Traditional transport models focus on short term decisions like route or mode choice. It is only logical that such models omit costs arising due to long term decisions because they are assumed constant. We argue that transport models to judge long term investment should include long term decisions and therefore additional utility components like those arising from location choice. This leads to the conclusion that travel time savings alone do not capture the utility gains appropriately in the long run.

Modelling more decision dimensions reveals higher utility gains. The reason is the higher flexibility of the actors, which allows them to adapt their choices more comprehensively.

Neglecting decision dimensions also prevents us to some extent from knowing who is going to profit from infrastructural investment. In this respect the simulations point at the fact that land price changes are influenced by improvements of transportation infrastructure and that models without location choice cannot capture this effect.

If we suppose behavioural dimensions to exist, we should model them and consider utility components directly influenced by them. This suggests that connection choice, departure time choice and location choice should be integrated because people are free to choose in these dimensions especially over a long term perspective. Otherwise it is likely that we are missing some consequences of an infrastructural investment. The results of this work suggests that

investments are misjudged in such cases. However, it depends also on the investment we want to evaluate which decision dimensions have to be considered.

When we model transport with discrete choice models, the indicator EMU allows us to capture all considered utility components and therefore all utility changes due to an infrastructural investment in a consistent way. Furthermore one can think of extending transport models to capture the consequences for the whole economic system as influenced by the transport system. In this case all utility components should be integrated as comprehensively as possible. The more utility components are considered in the EMU the better it is as a general indicator for welfare. Straatemeier and Bertolini (2008) therefore suggest the accessibility concept and the EMU as “common language” to be used by land use and transportation planners.

To assess the errors made in real assessments we have to consider realistic situations. This requires more detailed modelling and estimation of parameters using empirical input data. The right weighting of the utility terms considered is crucial because over all utility and consequently decisions depend on them. The parameters of the utility function should be estimated by stated preference or revealed preference surveys for sound results. However, the proof of concept model is able to show the qualitative differences in traffic flows and resulting utilities. It also shows what type of the errors we have to expect.

5.1 Critique of the Model

The approach with a simple MNL-Model does not account for the fact that two similar alternatives should have smaller joint probabilities. This shortcoming is critical in terms of connections with same links. The problem is similar to the red bus-blue bus problem (McFadden, 1974).

Further, it is unsatisfying to have discrete time options because the number of alternatives increases drastically when higher resolution in time is applied. Time resolution implemented becomes critical.

It is troublesome to deal with continuous quantities as choice dimensions inside discrete choice theory. On one hand a higher resolution promises exacter results, on the other hand higher resolution means more alternatives to be calculated resulting in longer computation

time. It will be necessary to develop heuristics for reasonable choice set generation if we want to simulate detailed real world scenarios. This means dropping the assumption of perfect information. The assumption that agents do not know about all alternatives is more realistic any way.

The algorithm for equilibrium calculation has some drawbacks. It cannot guarantee to find the SUE and it may get stuck in a local optimum. Furthermore it is not easily applicable for more complex networks.

5.2 Further Research

In this simulation changing location is as easy as changing departure time. Obviously this is not true. In reality there are costs associated with location change. Therefore location choice is more burdensome and consequently less frequent than connection or departure time choice. These issues should be considered if we want to have a better understanding of development processes in space and time. We will have to model the appearance of decision situations over time to interrelate short- mid- and long-term decisions. To simulate the adoption process of an urban system adequate in time, we have to consider the frequencies of decisions and durations of actions in more detail.

We can distinguish perceived and unperceived utility components. Think of utility produced by reducing emissions. Usually this utility component is unnoticed by the deciding traveller. In this case we would integrate it as unperceived component. If we want to simulate a scenario with an emission tax, we integrate the utility as perceived component. This way comprehensive models will also allow us to investigate situations in which the external costs are internalised. A main challenge will be to estimate the relevant costs correctly.

Furthermore, comprehensive models allow for a wider range of policies to be evaluated. A model with location choice, for example, allows to assess separately land use and transport policies with the same tool but – and more importantly – policy combinations. What is the effect of time dependent road pricing in combination with mixed land use?

6 References

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Appendix

Table 10 Model parameters

Name	Symbol	Value
Weighting parameter for travel time utility	β_r	0.27
Weighting parameter for utility from punctuality	β_t	-0.06
Weighting parameter for location choice utility	β_l	-0.05
VTTS	β_g	-1 or -2
BPR-parameter alpha main road link	α	0.7
BPR-parameter beta main road link	β	5
Travel time under free flow on main road link	T_0	3
Capacity of main road link per time interval	Q	27
BPR-parameter alpha highway link	α	0.4
BPR-parameter beta highway link	β	6
Travel time under free flow on highway link	T_0	2.5
Capacity of highway link per time interval	Q	40
Davidson-parameter iota	ζ	0.4
Travel time under free flow on railway link	T_0	3.5
Capacity of railway link per time interval	Q	33
Utility loss rate for SDE	ζ	$\beta_g - 0.1^4$
Utility loss rate for SDL	γ	20
penalty for being late	δ	5
Location occupancy rate sensitivity	λ	4

⁴ To avoid that agents choose longer travel time in favour of better punctuality, we require parameter ζ for utility loss rate for SDE to be smaller than the value of travel time.

Table 11 Calculated Indicators Respective to Choice Space

Average of 5 simulations	RTJ	RT	R	RJ	State 1
$\sum EMU$	1870.32	830.66	-1975.61	-1085.00	1567.40
$\sum V_r$	-1859.09	-1816.37	-1825.13	-1798.04	-1927.87
$\sum V_t$	-318.61	-339.35	-407.69	-420.24	-392.38
$\sum V_j$	-1040.00	-1173.33	-1173.33	-1015.51	-1173.33
$\sum V_{rj}$	-3217.70	-3329.06	-3406.15	-3233.79	-3493.58
\sum Travel time	24543.78	24083.77	24225.21	24065.41	25730.36
\sum Travelled distance	36468.8	35594.8	35594.8	36680.4	35594.8

Table 12 Coefficient of Variation of Occupancy rates

Out of 5 Simulations	Total	B		Total	C		Total	D	
		High	Low		High	Low		High	Low
RTJ	0.004	0.004	0.072	0.010	0.036	0.016	0.035	0.000	0.035
RT	0.005	0.009	0.171	0.005	0.271	0.014	0.041	0.000	0.041
R	0.005	0.009	0.171	0.005	0.271	0.014	0.041	0.000	0.041
RJ	0.004	0.010	0.140	0.010	0.128	0.018	0.032	0.000	0.032
State 1	0.005	0.009	0.171	0.005	0.271	0.014	0.041	0.000	0.041

Table 13 Coefficients of Variation of Calculated indicators

Average of 5 simulations	RTJ	RT	R	RJ	State 1
Σ EMU	0.00	0.02	-0.01	-0.01	0.01
ΣV_r	-0.01	-0.01	0.00	-0.01	-0.01
ΣV_t	-0.02	-0.02	-0.02	-0.01	-0.01
ΣV_j	-0.01	-0.02	-0.02	-0.01	-0.02
ΣV_{rj}	0.00	0.00	-0.01	0.00	-0.01
Σ Travel time	0.01	0.01	0.00	0.01	0.01
Σ Travelled distance	0.00	0.00	0.00	0.00	0.00

Table 14 Coefficients of Variation of Predicted Variations

Average of 5 simulations	Δ RTJ	Δ RT	Δ R	Δ RJ
Σ EMU	0.05	0.06	0.05	0.08
ΣV_r	0.22	0.17	0.10	0.08
ΣV_t	0.11	0.19	-0.44	-0.12
ΣV_j	0.08	0.00	0.00	0.16
Σ Realised utility	0.08	0.12	0.08	0.13
Σ Travel time	-0.20	-0.14	-0.13	-0.11
Σ Travelled distance	0.07	0.00	0.00	0.16

Table 15 Coefficients of Variation of Absolute and Relative Errors

Average of 5 simulations	F_{RT}	f_{RT}	F_R	f_R	F_{RJ}	f_{RJ}
ΣEMU	-0.07	-0.03	-0.10	-0.06	0.17	0.15
ΣV_r	0.31	0.42	0.41	0.57	0.21	0.41
ΣV_t	-0.34	-0.37	-0.08	-0.09	-0.08	-0.05
ΣV_j	-0.08	0.00	-0.08	0.00	0.61	0.59
Σ Realised utility	-0.11	-0.11	-0.11	-0.05	-0.93	-0.98
Σ Travel time	-0.35	0.48	-0.60	0.72	-0.36	0.52
Σ Travelled distance	-0.07	0.00	-0.07	0.00	0.63	0.61

Table 16 Coefficients of Variation of Changes in Predicted External Costs

Average of 5 simulations	ΔRTJ	ΔRT	ΔR	ΔRJ
Accident costs	-0.15	-0.09	-0.15	-0.24
Traffic noise costs	0.13	0.21	0.18	0.15
Air pollution costs	0.14	0.21	0.18	0.15
Climate costs	0.13	0.21	0.18	0.15
Sum external costs	-0.17	-0.10	-0.17	-0.37

Table 17 Coefficients of Variation of Absolute and Relative Error of Estimated External Costs by Choice Space

Average of 5 simulations	F_{RT}	f_{RT}	F_R	f_R	F_{RJ}	f_{RJ}
Accident costs	4.98	-10.72	0.21	-0.09	0.22	-0.12
Traffic noise costs	-0.08	-0.09	-0.38	-0.27	0.18	0.07
Air pollution costs	-0.10	-0.10	-0.38	-0.26	0.18	0.06
Climate costs	-0.08	-0.09	-0.38	-0.27	0.18	0.07
Sum external costs	-2.14	1.77	0.13	-0.09	0.51	-0.50