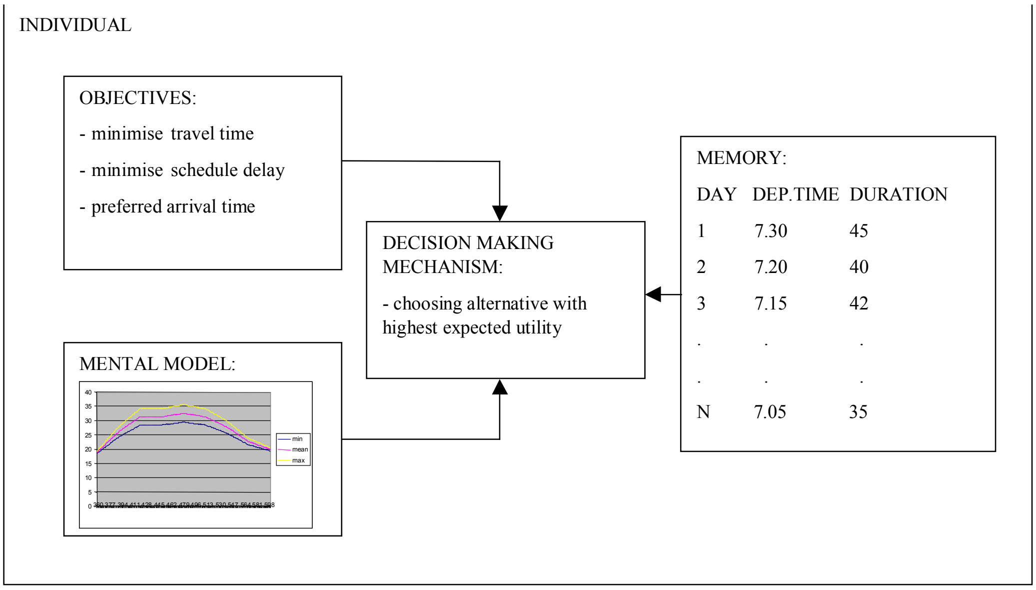

A micro-simulation model system of departure time and route choice under travel time uncertainty

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Abstract

Existing microscopic traffic models have often neglected departure time change as a possible response to congestion. In addition, they lack a formal model of how travellers base their daily travel decisions on the accumulated experience gathered from repetitively travelling through the transport network. This paper proposes an approach to account for these shortcomings. A micro-simulation approach is applied, in which individuals base their consecutive departure time decisions on a mental model. The mental model is the outcome of a continuous process of perception updating according to reinforcement learning principles. The individuals are linked to the traffic simulator SIAS-PARAMICS to create a simulation system in which both individual decision-making and system performance (and interactions between these two levels) are adequately represented. The model is applied in a case study that supports the feasibility of this approach.

Keywords

Micro-simulation, congestion, departure time choice, learning and adaptation

Preferred citation

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1. Introduction

Congestion is a major problem in urban areas throughout the world, causing both economic and environmental damage. Congestion occurs when the demand for travel exceeds the capacity of the existing road capacity at a certain location and at a certain time. Policies that are typically applied in urban areas to resolve (or at least reduce) congestion problems are often aimed at increasing the capacity of road infrastructure, by adding additional lanes or by optimising control systems (ramp metering, coordinated traffic signalling). In any case, the additional capacity is added to a complex traffic system, which is close to (or has already exceeded) system capacity. As a consequence, the behaviour of the system in response to minor changes in traffic demand or road capacity may be highly non-linear and chaotic.

A suitable way of describing systems in such states is the use of micro-simulation models. Micro-simulation models describe the behaviour of individual decision makers, but also the interaction between the system level and the individual, e.g. due to limitations in the capacity of the system. Micro-simulation models are, better than analytical models, able to model non-linearities in systems' behaviour under critical situations and have the advantage that the behaviour of individual actors can be specified in accordance with behavioural principles, found in physiology, psychology or economic science. A drawback of micro-simulation models has long been their computational requirements, but this argument has lost power in the light of improved computer technology. As a result, the last decade has shown the release of a considerable number of microscopic traffic simulators (Nagel, 2003) that are often available as commercial software packages. Nowadays, micro-scopic traffic simulation is commonly used in many practical situations (Mahmassani and Jayakrishnan, 1990; Anderson and Souleyrette, 2002; Klügl and Bazzan, 2003; Rossetti and Liu, 2003).

However, existing microscopic traffic simulators as used in applied traffic forecasting suffer from various shortcomings. Their behavioural scope is rather limited in the light of the problems to be modelled. In particular, departure time choice is often not modelled. Many publications (e.g. Jou et al., 1997; Rosetti and Liu, 1997; Kroes et al., 1996) emphasize the importance of departure time choice as a potential response to congestion. Ignoring departure time as a response to policies aimed at the reduction of congestion (which is common practice in applied micro-simulation modelling) may therefore lead to wrong outcomes and suboptimal solutions.

The literature in this area presents various micro-simulation models (or other assignment models) that include departure time choice (Van der Mede and Van Berkum, 1993; Hu and Mahmassani, 1997; Rossetti and Liu, 2003). However, these models do not contain a number of aspects that we feel are crucial for modelling the response to congestion appropriately. First, existing assignment models do not account for the effect of travel time uncertainty on departure time choice. This uncertainty may lead travellers to maintain safety margins in order to avoid late arrival. In general, travellers will balance the probabilities and consequences of both early and late arrival (Noland and Small, 1995). Ignoring the effect of travel time uncertainty will lead to a wrong assessment of the effect of congestion on departure time and the economic costs. Secondly, existing assignment models do not include a formal model of knowledge acquisition and cognition. This is crucial when analysing howdeparture time shifts take place in daily decision making, which makes up a large percentage of traffic in congested settings. In particular, without a solid representation of how new experiences are integrated in a traveller's cognitive system, his/her reaction to the experience is hard to predict. In this respect, we assume that each new experience is interpreted in the context of previous knowledge to assess whether behaviour should be adjusted. For example, a single 10 minute longer commute duration ina congested area will not prompt a traveller to change his departure time structurally, whereas 100 consecutive events of this type will have an effect on structural travel decisions. In other words, modelling travellers' cognition of both mean and variance of travel conditions is needed for modelling departure time adjustments properly.

Based on a more general theoretical framework (Arentze and Timmermans, 2003), this paper presents a micro-simulation model accounting for the above aspects. In this model system, individual decision makers decide about departure time for a routine trip, such as commuting, on consecutive days. Their decision making is based on a mental model of traffic conditions, specifying the mean and variance of travel time for various departure times. This mental model is updated once new experiences become available. The departure time decisions are fed into a SIAS-PARAMICS micro-simulation, simulating route choice and the resulting traffic flows, including delays due to congestion. The paper provides further details and is organised as follows.

Section 2 provides further information regarding the architecture of the mirco-simulation system. individual Section 3 provides more detail about the behavioural assumptions underlying the model. Both the information handling and storage and the decision making mechanisms are described. Section 4 describes the case-study in which the model was applied. Section 5 presents the results of the case-study, in terms of the effects predicted for various policies. Section 6, finally, draws conclusions regarding the approach and addresses avenues for further research.

2. The micro-simulation system

The model system consists of two important components:

1. Individual travellers;
2. the micro-simulation model SIAS-PARAMICS, which simulates the outcome of trip decisions of individual travellers.

In our model system, individual travellers are decision makers, who choose a departure time for a trip between a given origin and destination each day. Their aim is maximising the utility of their trip by minimising travel time and minimising schedule delays (early or late arrival) in relation to some preferred arrival time (PAT), e.g. the work start time. Their decision is based on a mental model of travel time, specifying for each departure time the mean travel time and the variability, expressed as the variance. The mental model is updated each day, after the outcome of the trip decision is known. The mental model is a function of the outcome of the new trip and the outcomes of previous trips, as stored in memory. Each individual has a memory, in which relevant aspects of previous trips are stored (such as day of the trip, departure time and duration). All previous trips are stored in memory, but not all are retrievable (see section 3), for instance because they are too old or are not considered to be representative. The basic components of the simulated individuals are displayed in Figure 1. Details regarding the behavioural processes of decision making, memory update en revision of the mental model are provided in section 3.

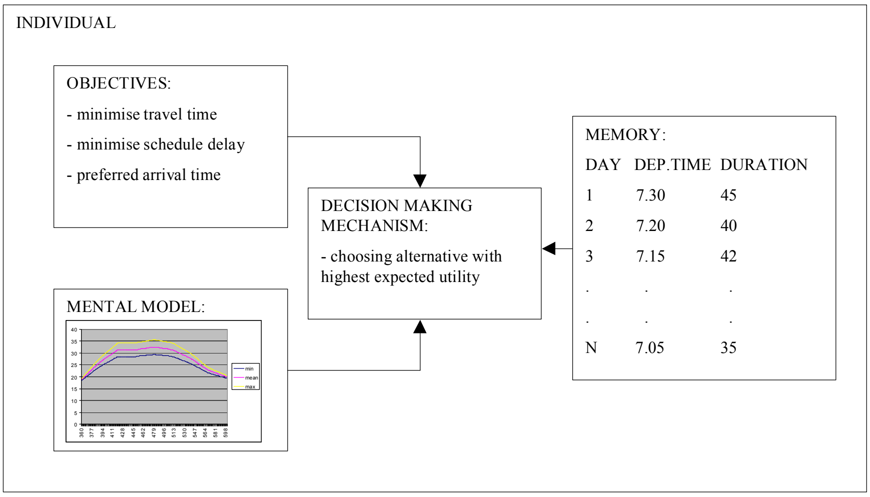

Figure 1: basic components individual model

The procedure through which individuals update their mental model and decide about departure time is displayed in Figure 2. Individual behaviour is conceptualised as a cyclic process of repetitively making departure time decisions and updating the perception.

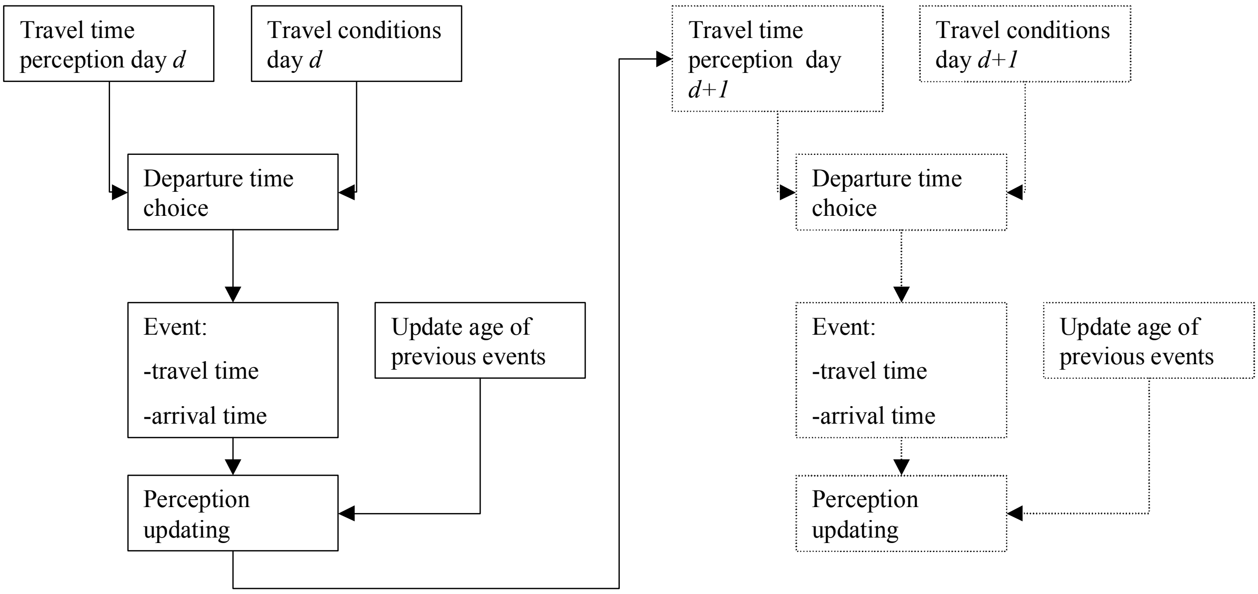

Figure 2: travellers' learning and perception updating process in the context of departure time choice

The starting point of the procedure for a given day is the existing perception of travel time and its variance as stored in the mental model. Next, a departure time is chosen, based on the existing mental model at day *d*. Thus, given an individual's mental model of the travel time, which is built up from previous experience, a departure time is chosen, aiming at realising an arrival time that is as close as possible to some preferred arrival time (*PAT*). In the context of the daily commute, the preferred arrival time is likely to be associated with the work start time. The outcome of the choice is a trip departing at some time *t*. The duration of this trip (and thus the arrival time) is considered to be the outcome of a stochastic process which depends to a large degree on the interaction with other individuals. The main factor in trip duration is the occurrence of congestion, which is determined by the decisions of other individuals to travel at particular times on particular routes. Hence, the trip duration experienced by a single individual depends ultimately on the mental models, experiences and preferences of other individuals. Once the trip is made and has resulted in some duration, the trip is added to the memory, and based on the memory, the mental model is updated. We assume that this updating process is guided by principles of reinforcement learning, which will be described in detail in the next section. The updated mental model is the base for travel decisions made on the next day, when a similar sequence of processes takes place.

The interaction between the individuals and the transport system is achieved by using individual agents in connection with the SIAS-PARAMICS microscopic traffic simulator. The traffic simulator is used to simulate individual trips of car drivers through a transport network, based on a dynamic OD-matrix. The simulation involves the route choice between origin and destination, and details of the driving behaviour, such as speed (responding to other cars on the network) and lane choice. The input of SIAS-PARAMICS consists of (Figure 3):

1. an OD matrix;

2. flow profiles for each OD relation, specifying for each departure time interval the percentage of trips departing in that time slot;

3. a transport network, specifying physical lay out of the road network, and including signalling systems.

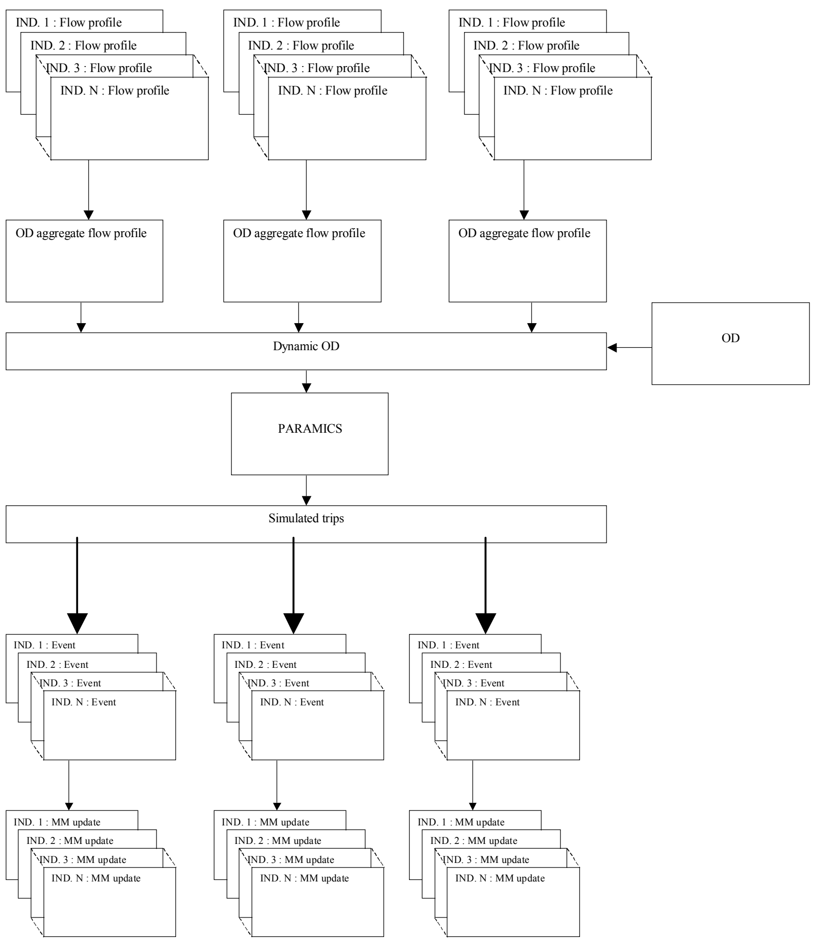

Figure 3: structure of micro-simulation system

For each OD pair a number of individual travellers is defined. These individuals travel between the given origin and destination each day. Each individual has a specific preferred arrival time (PAT). The distribution of PATs across individuals for each OD pair should follow a logical form, based on the literature in this area. Ideally, the number of individuals should equal the number of trips per OD. In this stage of development, this was technically infeasible, so that we settled for a much smaller number of individuals per OD (4), enabling to demonstrate the principles of our approach. Given an individual's PAT, the choice mechanism (see section 3) is such that a choice probability is calculated for each departure time. The resulting probability density function is interpreted as a flow profile for travellers with that specific PAT. The flow profiles of individual individuals are integrated to a flow profile on the aggregate OD level, by summation. The OD flow profiles are combined with a predefined static OD matrix to provide the input for a regular SIAS-PARAMICS simulation procedure. Note that we assume the static OD matrix to be constant throughout the learning process. That is to say, we assume that trip generation, destination and mode choice are constant, and that learning and adaptation takes place only with respect to departure time choice and route choice. Further, it should be noted that only the departure time choice is modelled as an explicit learning and adaptation algorithm, taking into account the knowledge of the individual. Route choice is modelled inside SIAS-PARAMICS, and assumes that full information regarding travel times on various routes is available.

The SIAS-PARAMICS simulation results in (among other things) a listing of simulated trips, specified by origin, destination, departure time and arrival time. From these data, events are extracted for each individual. In particular, given OD and departure time, the trip duration is derived from the listing of trip durations. Based on the event, the mental model is updated.

Thus, central to our approach is that we use a sample of individuals to represent the learning and adaptation behaviour of the total population of travellers on an OD relation. Hence, it is important that the individuals represent the total population well, in terms of learning and adaptation behaviour. This applies to preferences such as PAT, value of travel time and sensitivity of delay, but also to cognitive parameters such as speed of learning or learning strategies. In this study, we varied only the PAT, while keeping other behavioural parameters constant across individuals.

The individuals are operationalised as databases in which memory, mental model and behavioural parameters are stored. The individuals' behaviour is invoked by specific executable files that are run from batch files and manipulate the databases. Dedicated programmes take care of the integration of individual data into SIAS-PARAMICS input and the disaggregation of SIAS-PARAMICS output to individual individuals.

3. Behavioural models

The general model structure described above contains both cognitive and decision making processes, which are described in more detail in this section. It is derived from a general framework about learning and adaptation (Arentze and Timmermans, 2002), and follows on previous work (Ettema, Arentze and Timmermans, 20003)

3.1 Events

We assume that a traveller's perception is derived from a series of consecutive experiences, termed "events". In our model these events are daily morning commute trips. Formally an event can be represented as:

$$e = (\mathbf{x}, \mathbf{r}, d, \rho, w) \tag{1}$$

where:

x is a vector of attribute values describing the event;

r is a vector of reward values or outcomes related to the event;

d is an index of the time (a day) at which the event took place;

ρ is the memory strength of the event;

w is a weight associated with the event.

In our model of perception updating, the attributes **x** can be considered as the conditions under which a commute trip takes place, and which serve to classify trips into mental classes with respect to their expected reward. Potential attributes of this kind are departure time, day of week, weather conditions and the presence of traffic information. In our model we included only departure time as a condition. Associated with each event is a vector of outcomes **r**. The outcome considered in this study is the trip duration, implying that the aspect about which travellers learn is travel time.

The memory strength ρ represents the ease with which an event can be retrieved from memory. An event is considered to be retrievable if the memory strength ρ exceeds some threshold value. Retrievability is relevant for the process of identifying the conditions under which events have similar outcomes. Only if an event is retrievable it is included in this *induction* process. Memory strength ρ is defined as a function of the recency ζ of an event, but also of the representativeness η, which expresses the difference between the realized and the expected outcome of an event. For instance, if travel time at 7.00 AM is usually 30 minutes, but is 60 minutes on a particular day due to a large incident, the experience of 60 minutes can be regarded as non representative for the usual situation and be ignored in perception updating. Thus memory strength ρ is defined as:

$$\rho = \eta * \zeta \tag{2}$$

Representativeness η is defined as a function of expected travel time t^e (the mean travel time for a certain departure time stored in the mental model) and realized travel time t^r.

$$\eta = \left(1 - \frac{abs(t^e - t^r)}{t^e}\right)^{\lambda} \tag{3}$$

Recency is considered a function of the time *d* associated with the event and the current time d_0. In equation:

$$\zeta = f(d, d_0) \tag{4}$$

From a behavioural point of view, the recency included in the weight may represent different learning strategies. In a non-stationary environment, it may be a good strategy to assign a smaller weight to older events, as these are not representative of the current and future situation. Larger values of α then lead to quicker adaptation to changes in the environment. In a stationary environment with random fluctuations (which is the case in this study) recency affect the speeds with which one learns about the environment, given some biased a priori expectation. Larger values of α increase the speed of learning, but at the risk of making larger mistakes in the earlier stages of learning.

There are many potential functional forms to represent recency, based on the assumption that recency decreases with the age of the event, but differ in the speed and curvature of memory decay. For a review of potential memory decay functions, the reader is referred to Timmermans *et al.* (2003). In this study, we assume that individuals learn by classifying events into mental classes to discriminate between the states or conditions that generated particular outcomes. Assume that in state S_d events are grouped into n classes $\{c_1, c_2,\ldots, c_n\}$. For each class c, events are ordered with respect to their age ($d_0 - d$), and each event e is assigned a rank order q_{ec}. Thus, $q_{ec}=m$ implies that event e is the m^{th} newest event in class c. The recency of an event e in class c is then calculated as:

$$\zeta = (1/q_{ec})^{\alpha} \qquad (5)$$

Thus, the recency of an event depends on both the recency of the event and the class in which it is grouped. α represents the speed of memory decay.

An event is retrievable only if memory strength exceeds some threshold value τ :

$$\rho \geq \tau \qquad (6)$$

Attached to each event is also a certain weight, indicating the importance of the event in the memory updating process. As for the memory strength, we assume that the weight is affected by the recency of the event and the representativeness. Consequently, the weight is defined as:

$$w = \left(1 - \frac{abs(t^e - t^r)}{t^e}\right)^{\mu} * (1/q_{ec})^{\chi} \qquad (7)$$

3.2 Mental model updating

We assume that an individual's mental model of travel time encompasses not only the perception of the travel time, but also of the uncertainty of the expected travel time. The uncertainty is expressed as the variance of travel time. Because trips are made under a variety of conditions that can influence the outcome of the trip (the travel time), an individual's mental model will include the mean and variance of travel time under these respective conditions (e.g. departure time, presence of traffic information). Thus, the travel time T and standard deviation σ can be specified specifically for a set of conditions $\{c_1, \ldots c_n\}$ as $T_{c_1 \ldots c_n}$ and $\sigma_{c_1 \ldots c_n}$. It is assumed that travellers base their perception of T and σ on the events stored in memory. However, given limitations in the capability of humans in processing and storing information, individuals will not store information for all possible conditions, but will only distinguish between condition states that are significantly different in terms of the outcome of the event. In other words, we assume that travellers classify their experiences to differentiate between travel conditions for which the expectation of travel time is relatively comparable.

We modelled this process by using existing CHAID-algorithms for decision tree induction. In this procedure, departure time and the presence of traffic information serve as predictor variables, whereas the travel time is the target variable. In the calculations, the events are weighted according to the weight factor w defined previously. Figure 4 gives an illustration of the possible classification. In this figure, the mean travel time across all events is 21.5 minutes and the standard deviation is 6.7. However, three subclasses are identified which differ significantly with respect to the expected travel time. Also the standard deviations differ between classes.

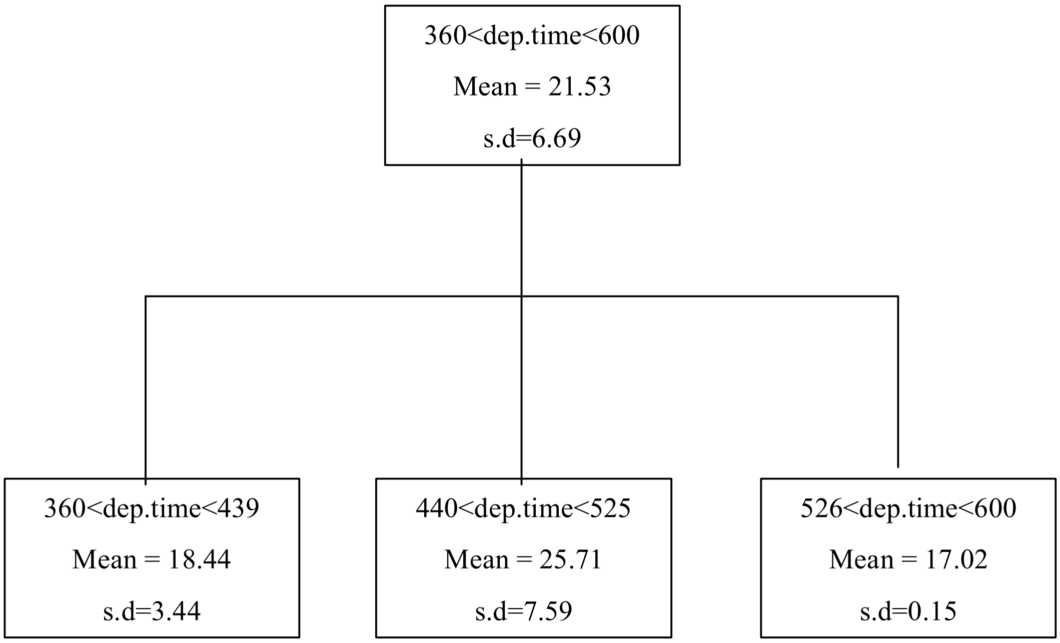

Figure 4: example of classification of trips according to travel time

3.3 Departure time choice

We assume that when choosing a departure time, individuals aim at realising an arrival time that is as close as possible to some preferred arrival time (*PAT*). In the context of the daily commute, the preferred arrival time is likely to be associated with the work start time. In addition, we assume that travellers will try to minimise travel time. Following Small (1982), the utility of a trip departing at *t* can then be specified as:

$$U_t = \beta_1 * T_t + \beta_2 * SDE + \beta_3 * SDL + \beta_4 * L \tag{8}$$

In this equation, T_t is the travel time when departing at time *t*. *SDE* and *SDL* are the early and late schedule delay respectively. The schedule delay is the amount of time one arrives before or after the preferred arrival time *PAT*. Thus:

$$SDE(t, T_t, PAT) = max((PAT - t - T_t), 0) \tag{9}$$

$$SDL(t, T_t, PAT) = max((t + T_t - PAT), 0) \tag{10}$$

L is a dichotomous variable indicating late arrival:

$$L = \begin{cases} 0 & \text{if} \quad t + Tt < PAT \\ 1 & \text{if} \quad t + Tt > PAT \end{cases} \tag{11}$$

L denotes the constant disutility of late arrival, representing the discomfort of late arrival per se, irrespective of the amount of delay. However, in an individual's perception, travel time T_t is not a constant value but a stochastic variable, defined by μ_t and σ_t. It is assumed that based on this perceived probability distribution, individuals form an expected utility for a tip departing at *t*, specified as:

$$EU_t = \int_{T\min}^{T\max} \begin{array}{l} [\beta_1 * T_t \; + \beta_2 * SDE(t, T_t \; , PAT) + \\ \beta_3 * (t, T_t \; , PAT) + \beta_4 * L(t, T_t, PAT)] f(T_t \;) d(T_t \;) \end{array} \tag{12}$$

where $f(T_t)$ is normally distributed with $N(\mu_t, \sigma_t)$. In the expected utility, individuals account for uncertainty in travel time by weighting each outcome by its probability. Finally, it is assumed that an error term ε_t is associated with each expected utility EU_t . Assuming that the error terms are IID distributed, the choice of departure time is then described by the well known logit model:

$$P_t = \exp(EU_t) / \sum_k \exp(EU_k) \tag{13}$$

It is recognised that the IID assumption may be too strong an assumption, because of similarities between choice alternatives. However, that discussion is beyond the scope of this paper. The model described above was applied using parameter values reported by Small (1982):

$$\begin{array}{ll} \beta_1(T_t) & = -0.106 \quad (1/\min) \\ \beta_2(SDE) & = -0.065 \quad (1/\min) \\ \beta_3(SDL) & = -0.254 \quad (1/\min) \\ \beta_4(L) & = -0.58 \end{array} \tag{14}$$

4. Case study

The multi-individual model system was implemented based on an existing SIAS-PARAMICS study for the N57 in The Netherlands. In this study traffic flows during the morning peak on the trajectory of the N57 between the N496 and the Caland bridge near the A15 were modelled. The N57 is a provincial main road with a series of cross roads. The model consists of 8 traffic zones and a rather linear network (see Figure 5). In the current situation, there is moderate congestion on the N57. The Caland bridge is opened twice in the morning peak (at 7.10Am and 8.30 AM) leading to additional delays.

In the existing model, OD matrices were based on traffic counts for the morning peak period (6.00AM-9.00AM). The flow profiles used in the existing model were rather flat, leading to an even distribution of trips across time. However, in the current study, we assumed that preferred arrival times varied between 7.30AM and 9.00AM, leading to a concentration of travel demand in time. As a consequence, we downscaled the OD matrix in order to obtain realistic traffic flows. The new OD matrix contains 10.118 vehicles.

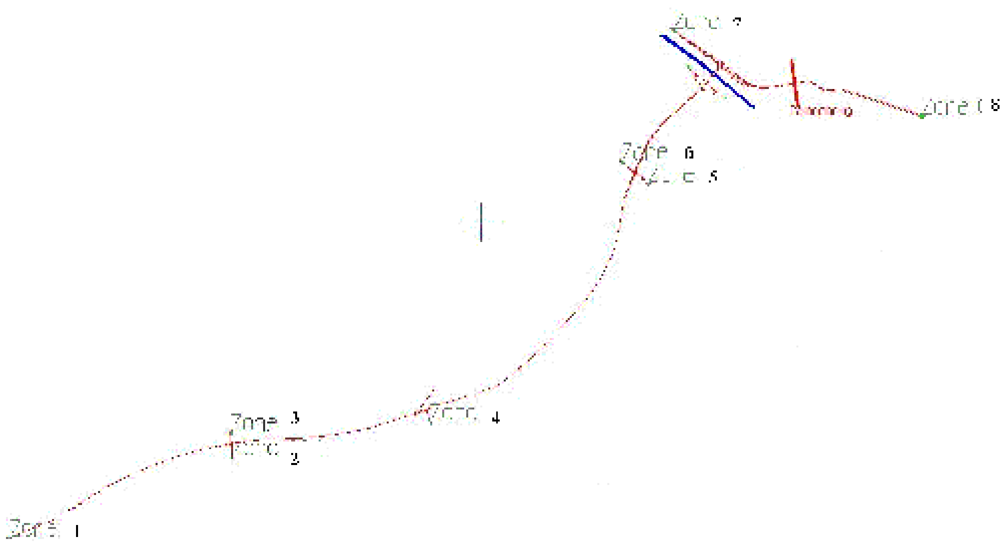

Figure 5: simulation network

To implement the system, 4 individuals were defined for each OD pair. Individuals were only defined for relationships in the congested west-east direction. Excluding intrazonal trips, this results in 112 individuals in total. Individuals represent only personal traffic. Freight traffic is assumed to be fixed and does not change departure time in response to congestion. For each OD pair 4 PATs were used: 7:30, 8:00, 8:30 and 9:00. All individuals were weighted equally in constructing the overall flow profile for each OD. Otherwise all individuals were identical in terms of behavioural parameters. The behavioural parameters were derived from an exploratory study (Ettema et al., 2003), in which they produced plausible results. The parameters are displayed in Table 1. Each simulation consists of 40 time steps (consecutive days).

Table 1: parameter settings used in the micro-simulation

Parameter	Value
α , χ	0.50
λ , μ	0.80
the significance level required when splitting or merging groups of events based on some predictor variable	0.10
the minimum number of observations (in this case events) required for a parent node	2
the minimum number of observations (in this case events) required for a parent node	2

5. Results

Looking at the simulation results on aggregate, it can be concluded that the learning and adaptation mechanism leads to a change in departure time patterns in response to the occurrence of congestion. However, this change differs considerably between ODs. A general pattern that emerges is that the change in departure times is larger for upstream origins, than for downstream origins. To illustrate this difference, the shifts in flow profiles for ODs 1-8 and 6-8 are displayed in Figures 6 and 7. The figures display for each departure time the share of trips departing in a one-minute interval, for the first and the last time step.

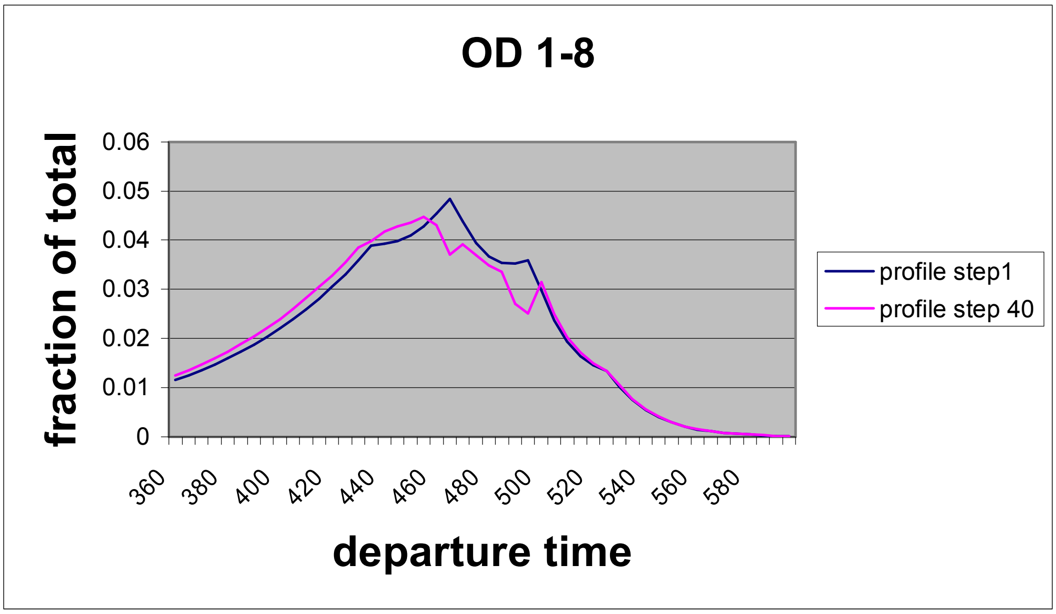

Figure 6: shift in flow profile OD 1-8

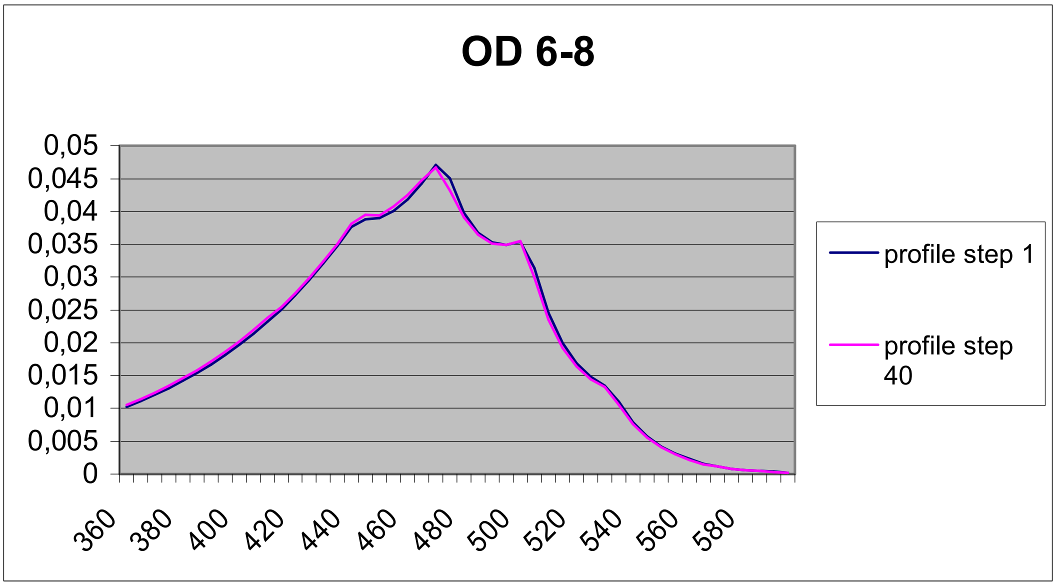

Figure 7: shift in flow profile OD 6-8

The larger shift in departure times for upstream origins is logical given that trips departing from these origins use the congested network over a longer distance, and consequently face more serious congestion and travel time uncertainty. Larger adjustments are then necessary in order to gain an acceptable trip utility.

One question is to what extent the changes in OD-pairs lead to more efficient use of the road network and avoidance of congestion. To answer this question, the mean travel times for each OD were calculated for the first time step (without adjustment of departure time) and the last time step (with adjustment of departure time). The results are displayed in Table 2.

Table 2: change in travel time for some important ODs

OD-relation	# trips	Mean travel time time step. 1 (sec.)	Mean travel time time step. 40 (sec.)	Difference
1-2	54	210	227	17
1-3	52	227	241	14
1-4	14	385	408	23
1-5	2	649	557	-92
1-6	16	619	665	46
1-7	53	780	814	34
1-8	713	887	903	16
2-3	92	36	38	2
2-4	7	120	124	4
2-5	2	386	411	25
2-6	17	355	365	10
2-7	4	526	499	-27
2-8	113	603	608	5
3-4	11	138	141	3
3-5	2	387	383	-4
3-6	2	360	379	19
3-7	1	497	591	94
3-8	216	633	630	-3
4-5	23	257	252	-5
4-6	299	249	249	0

4-7	48	368	364	-4
4-8	250	493	480	-13
5-6	376	69	69	0
5-7	131	169	166	-3
5-8	117	306	292	-14
6-7	27	288	253	-35
6-8	1309	446	373	-73
7-8	1779	191	188	-3
TOTAL	5730	379	363	-16

The results indicate that travel times from upstream origins (1-3) increase, whereas travel times of trips from downstream origins (4-8) decrease. This suggests that the change in departure time observed for upstream locations does not result in a reduction of travel times for those origins themselves, but is beneficial for trips departing from downstream origins. A better temporal spread of upstream departures thus leads to higher average travel speeds downstream. The downstream origins profit from this. This phenomenon is illustrated by the travel time, which is plotted as a function of departure time in Figures 8 and 9. For OD 1-8, travel times increase in the period between 420 (7.00AM) and 480 (8.00 AM), when the bulk of trips is made. For OD 6-8, travel times decrease in the period between 460 (7.50 AM) and 520(8.50 AM), because fewer trips depart in this period from upstream locations.

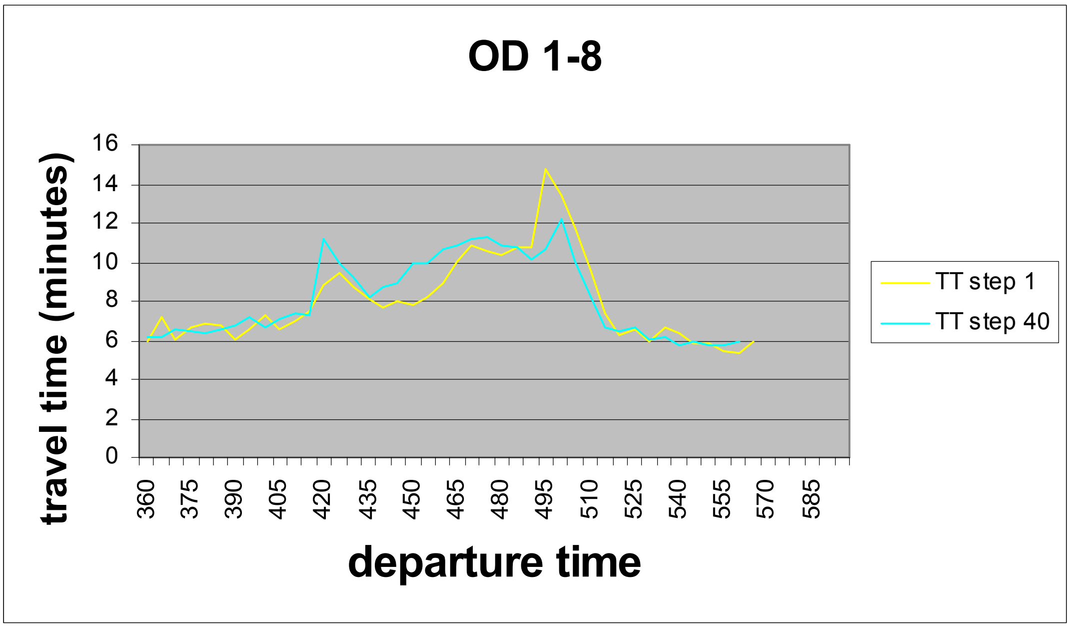

Figure 8: travel time as a function of departure time for OD 1-8

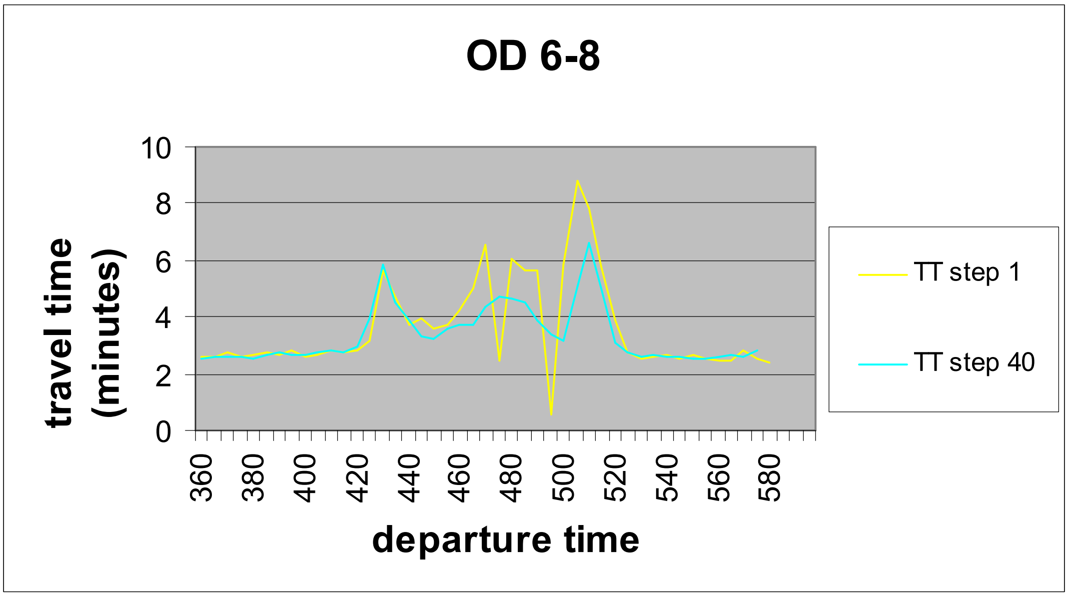

Figure 9: travel time as a function of departure time for OD 1-8

The fact that trips from upstream origins take more time after 40 time steps does not automatically imply that their performance has worsened. It is possible that the average trip utility has increased, for instance because schedule delays are avoided. To analyse this effect, the outcomes of decisions of individual individuals were analysed with respect to:

1. the travel time;

2. the utility of the trip.

Figure 10 displays these items as a function of the time step for the OD relations 1-8 and 6-8. Each figure displays the development for agents with different preferred arrival times (PAT): 7.30 AM (450), 8.00 AM (480), 8.30 AM (510) and 9.00 AM (540). A first finding is that day-to-day variations in travel time are considerable. This holds even more for trip utility. This is caused by the fact that departure time choice of individuals is modelled as a stochastic process, which leads to incidental outliers, i.e. very early or very late departures. However, also for similar departure times, travel times and trip utilities vary considerably, due to the travel time uncertainty that is typical for congested networks. Based on these figures, it is very difficult to assess whether or not individuals increase their trip utility through learning and adaptation. In any case, there is not a clearly increasing trend in trip utility. A possible explanation is that the stochastic nature of departure time choice and of the traffic simulation results in fluctuations that are larger than the utility to be gained from better informed decision-making. However, inspection of the mental models of individual travellers learns that the representation of travel times has improved for a majority of the agents. The number of individuals modelled in this study is too small to test whether trip utility increases on an aggregate level. Future work will therefore include analyses with a larger number of modelled individuals, to find out how individual learning depends on the degree of travel time variation.

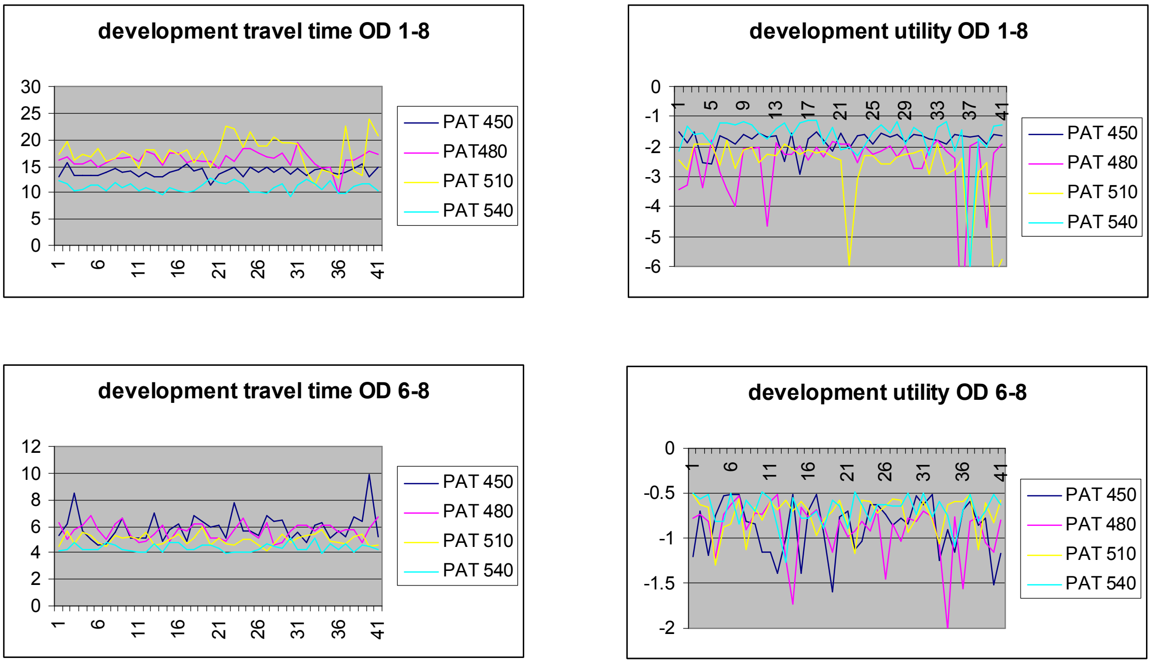

Figure 10: development of trip performance of various individuals

Overall, the simulation results suggest that the individuals (and through them the system as a whole) respond to experienced trip outcomes by changes in departure time. Although the departure time changes are made with the aim of increasing trip utility in the light of acquired knowledge of the travel conditions, the benefits of departure time change are not straightforward. First, the analysis of travel times at the beginning and at the end of the simulation procedure suggest that those benefiting from the departure time change are not the ones who switch departure time. In particular, trips departing from upstream origins change departure time but face increasing travel time, whereas downstream origins do not switch departure time but experience decreasing travel times. Second, the analysis on the individual level does not show a clear increase in trip utility (or a decrease in travel time). Although the modelled individuals improve their perception of the travel conditions, this does not readily result in improved trip outcomes. A possible explanation is the uncertainty in travel conditions, which make travel time the outcome of a stochastic process. This result is in line with results of similar simulations in a more simplified setting (Ettema et al., 2003).

6. Conclusions

In this paper we have proposed a traffic assignment procedure that is an extension to the existing practice in a number of ways. First, it allows for the adjustment of departure time in response to congestion. Second, it models departure time choice as a function of both mean and variance of travel time at different possible departure times. By this, the effect of travel time uncertainty is accounted for. Third, it uses a representation of travellers' mental model of travel circumstances that serves as a base for departure time decisions and is daily adjusted in the light of new experiences. Through this, learning and adaptation effects are represented.

An application of the model system to a small case study has illustrated the potential of the model in predicting the responses to congestion in a realistic way. Peak spreading effects could be represented in a realistic way. In this respect, not only mean travel time but also the variance serves as an explanatory variable, which is considered an improvement over existing approaches, given the increasing emphasis on travel time reliability. The learning and adaptation procedure that is used appeared to be realistic in the sense that travellers gradually improved their perception of the travel circumstances. However, the simulation results suggest that the outcomes of the learning and adaptation process may not be straightforward. First, the benefits from behavioural adaptation may not accrue to those who adjust their behaviour but to others. Second, an improvement of trip utility on the individual level was not clearly observed. We believe that the learning and adaptation procedure is a powerful tool in modelling the dynamics in responses over time. This will become particularly important in case of non-stationary traffic situations, for instance if traffic conditions gradually worsen. The procedure proposed here can then be used to model delays in travellers' responses.

Future work should include a number of directions. First, the behavioural parameters need to be better underpinned. One way of doing this would be to conduct experiments where travellers learn and adjust in a controlled laboratory setting. It will be important to also represent different types of decision makers, such as early adaptors, risk takers and risk avoiders, optimising and satisficing travellers etc. Another important issue concerns the understanding of learning behaviour under uncertain circumstances. The simulations conducted in this study suggest that travellers' perception of the environment improves through the learning procedure, but that this does not result in higher trip utility. Further tests are necessary to understand the relationship between travel time uncertainty and trip performance in learning processes. In addition, a better insight is needed in the effects of the procedure on system performance. For instance, it is interesting to know which individual learning strategies lead to better system performance and how travellers can be persuaded to follow such strategies. Finally, further work will be done on the practical implementation of the procedure on a larger scale, in particular by using larger networks and larger numbers of individuals.

7. References

Anderson, M.D. and R.R. Souleyrette (2002), Pseudo-dynamic travel model application to assess traveler information, *Transportation*, **29**, pp. 307-319.

Arentze, T.A. and Timmermans, H.J.P. (2003), Modeling learning and adaptation processes in activity-travel choice: a framework and numerical experiments, *Transportation,* **30**, 37-62.

Ettema, D, T. Arentze and H. Timmermans (2003), Modelling perception updating of travel times in the context of departure time choice under ITS, Paper presented at the Euro-workshop "Behavioural Responses to ITS", Eindhoven, 1-3 April 2003.

Ettema, D, H. Timmermans (2003), Costs and benefits of travel time uncertainty and travel time information: conceptual model and numerical examples, submitted to *Transportation Research C*.

Hu, T-Y. and H.S. Mahmassani (1997), Day-to-day evolution of network flows under real-time information and reactive signal control, *Transportation Research C*, **5**, pp. 51-69.

Klügl, F. and A.L.C. Bazzan (2003), Route decision behaviour in a commuting scenario, paper presented at the Euro-workshop "Behavioural responses to ITS", April 1-3, Eindhoven.

Kroes, E., A. Daly, H. Gunn and T. van der Hoorn (1996), The opening of the Amsterdam Ring Road. A case study on short-term effects of removing a bottleneck, *Transportation* **23**, pp. 71-82.

Mahmassani, H.S. and R. Jayakrishnan (1991), System performance and user response under real-time information in a congested traffic corridor, *Transportation Research A*, **25**, pp. 293-307.

Mede, P.H. van der and E.C. van Berkum (1993), The impact of traffic information: dynamics in route and departure time choice, Delft University of Technology.

Nagel, K. and B. Raney (2003), Large scale multi-agent simulations for transportation applications, paper presented at the Euro-workshop "Behavioural responses to ITS", April 1-3, Eindhoven.

Palma, A.de and F. Marchal (2001), Real cases applications of the fully dynamic METROPOLIS tool-box: an advocacy for large-scale mesoscopic transportation systems. Submitted to Networks and Spatial Theory.

Rossetti, R.J.F. and R. Liu (2003), A multi-agent approach to assess drivers' responses to pre-trip information systems, paper presented at the Euro-workshop "Behavioural responses to ITS", April 1-3, Eindhoven.

Small, K.A. (1982), The scheduling of consumer activities: work trips, *The American Economic Review*, **72**, pp. 467-479.

Timmermans, H., T. Arentze and D. Ettema (2003), *Learning and adaptation behaviour: empirical evidence and modelling issues*, paper presented at the Euro-workshop "Behavioural Responses to ITS", Eindhoven, 1-3 April 2003.