

Effects of Advanced Traveller Information Systems on Commuters' Behaviour

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Abstract

A genetic algorithm approach is used to study the behaviour of agents in a simulation of a daily route choice. There are two roads to choose and we show that there is a welfare enhancing effect of an Advanced Traveller Information System (ATIS) in comparison to the standard case without an ATIS. In the first case it is remarkable that not all agents follow the recommendation of the ATIS and the equilibrium distribution is only approximately attained.

Keywords: traffic, computational economics, genetic algorithm, action trees, multi agents systems, simulation, traveller information system

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Content

1	Introduction	1
2	Action models	1
2.1	Basic model	1
2.2	Basic model extended by ATIS	2
3	The genetic algorithm	3
4	Results	4
4.1	Calibration	4
4.2	Basic model	5
4.3	Basic model extended by ATIS	6
5	Conclusions	8
6	Appendix: Specifications	9
6.1	Parameters, variables and constants of the decision tree	9
6.2	Decision tree	9
6.3	Nodes	10
7	References	11

1 Introduction

With an increasing amount of traffic world wide (NSTC (1999)), congestion is a daily routine for many travellers and commuters and it is unlikely that this situation will change for the better for many traffic systems in the near future (BVBW (2001)). To solve the problem it becomes more important to supply Intelligent Transportation Systems (ITS), which lead to a better usage of available traffic networks. Kwan and Golledge (1998) emphasise that Advanced Traveller Information Systems (ATIS) are a key factor for the implementation of successful ITS.

This paper examines how individual drivers react on information from an ATIS, in a situation of daily home-to-work-route choice.

Mahmassani et al. (1997) differentiate three possible reactions of work commuters on peak period congestion: First, variations of the departure time, second, changes in frequency, purpose, and duration of intervening stops and third, selecting a different route. These testimonies are based on an empirical study in Austin, Texas.

Another study presented by Stern et al. (1998) investigates commuters' behaviour in the Netherlands. In congruency with Mahmassani's result, the most common reaction is a variation in the working time, which results in a variation of trip starting time, and a variation of route to/from work. Other observable reactions are increasing home working activities, increased usage of public transportation, job changes and changes of home locations.

In chapter 2 we describe a simple model of route choice under influence by an ATIS, in chapter 3 a genetic algorithm to simulate agents' behaviour is described and in chapter 4 we present results of some simulations of agents' behaviour within our model.

2 Action models

To study the effects of an ATIS, we use two models to capture the effects of the genetic algorithm. First, we set up a basic model of agent behaviour without an ATIS and second we extend this model by an ATIS.

2.1 Basic model

The basic model consists of agents who have two route options to drive to work. So they have to decide between two roads, which differ in their transport capacity. In the following they will be called: S_{big} and S_{small} . There is no outside option, neither short term orientated as using public transport systems or not going to work, nor long term orientated as moving nearer to working place or getting another job. The resulting action tree is shown in figure 1.

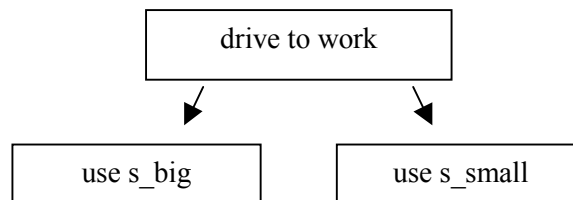


Figure 1: basic model action tree

The agents decide in a random order, the numbers of agents driving on S_{big} respective S_{small} are call n_{big} and n_{small} . The resulting agent's utility is equal to the use under perfect circumstances – no other drivers on the road – minus the time lost by other drivers jamming the road. S_{big} enables a greater utility under perfect circumstances and is less affected by higher utilisation. Altogether this model is very similar to the experiment described by Selten et al. (2005).

2.2 Basic model extended by ATIS

Now we introduce an ATIS in form of a traffic radio in our model. After a specific number of agents have decided on which route to take, a route recommendation is given. This recommendation consists just of the information which route would actually yield to a higher utilisation. As the interval of recommendations gets smaller, the quality of the ATIS should improve.

The decision tree is then modified to give reaction options to the recommendation. First the agent has to decide whether he believes in the recommendation or not – in the latter case he will decide in the same way as in the basic model. If he believes in the recommendation, on the one hand he could directly follow this recommendation or on the other hand respond in the contrarian way. Figure 2 shows the corresponding action tree.

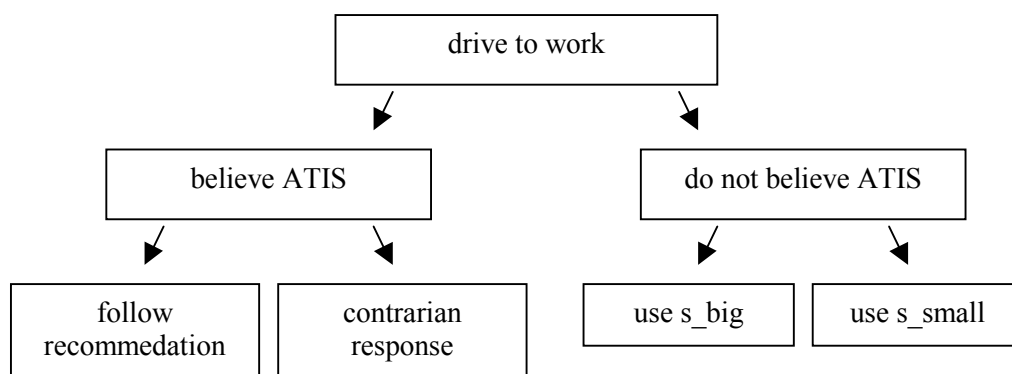


Figure 2: extended model action tree

3 The genetic algorithm

To get dynamics into the simulation, a genetic algorithm is used to change the agents' action attributes. Each attribute has a binary code which is called 'gene' in the following. A set of genes makes up a gene pool.

Following Pitz (2005) a genetic action tree $G(T)$ is defined as:

1. T is an action tree.
2. For each agent, action type and attribute $C(i, a)$ is the gene pool (a set of bits).
3. For each action type, there exists a decision degree, which is a probability for choosing that action type. There might be a condition Δ if the action type (a special node in the action tree) is disabled. For instance, the agent might be willing to buy something, but is out of money.
4. For each gene $c(i, a)$ out of $C(i, a)$ there exists a fitness function $\varphi(c(i, a))$, which is determined contingent of the outcome of the action.
5. $\delta(c(i, a))$ is the semantic of $c(i, a)$, which describes the contingency of the action in respect to the gene in the simulation.

If the agent is not obliged to a certain action, it will follow the action tree from the root to the leafs. Every attribute of each action type with its coded value $c(i, a)$ will be filled using a uniform distribution. A violation of the condition Δ_{H1} or Δ_{H2} will cancel the sub-nodes $H1$ or $H2$ respectively¹. This is the way we have chosen to force the agent to do a certain action, if necessary.

In the case that there are two choices left, the gene pool is used to determine the agent's action. A $c(i, a)$ is taken out of the gene pool $C(i, a)$ (again by a uniformly distributed probability) and if $\delta(c(i, d_{h1})) < d_{h1}$, then the left node is chosen and vice versa.

Reaching the root of the decision tree, every action attribute has its coded value $c(i, a)$ and each of them is evaluated by the fitness function $\varphi(c(i, a))$ dependent on the outcome when the agent has run the action tree.

Since every gene now has a certain value, the action is specified and can be carried out. Each action changes the environment and this will be the evaluation basis for the fitness φ of the agent's action attributes.

Three principles are used by the genetic algorithm: mutation, selection and cross over.

¹ $H1$ denotes the "left" node, $H2$ the "right" node.

A mutation is created by a mutated copy of a gene which is changed at ‘selected’ random places. With a probability p (which is in our case anti-proportionally related to its fitness) the agent’s gene will be replaced by this mutation. The better its fitness, the lower is the probability of changing the gene.

When all the genes of each agent are assembled to one large gene pool, 5% of this gene pool is randomly mixed by a cross over, that is, one set of genes is taken to another location and the former set is overwritten by the replaced set.

We used a general framework developed in a seminar at the Laboratory for Experimental Economics, University of Bonn, intended for use with genetic action trees. Instead of setting the fitness immediately after each agent’s choice, the fitness of the decision genes is calculated after the activation of all agents for each genetic cycle. In our model the fitness of every agent’s decision gene is the sum of utilities of this agent over a genetic cycle.

4 Results

We now combine our agents’ action models with the genetic algorithm and make some behaviour simulations. We begin with some simulation calibrations, then we go on to present some results for the basic model and finally we introduce the ATIS in two different quality levels.

All results we present in this section come from simulation runs of the genetic algorithm. If something is said to be significant, it is in the context of a t-test at the 5%-level.

4.1 Calibration

Each run of the simulation covers 200 rounds with 100 agents. Every 10 rounds the genetic algorithm is called and the mutation is done – the genetic cycle. The other parameters of the framework are set to their default values, too. Just to mention the basic setup, every decision degree is set to 50 per cent.

The implemented utility function for an agent using S_{big} is:

$$U_{big} = 3.50 - 0.02 * n_{big}$$

For the other agents, who are driving on S_{small} , the utility function is:

$$U_{small} = 3.00 - 0.03 * n_{small}$$

For this utility functions an equilibrium and a first best solution could be determined. In equilibrium 70 agents should use S_{big} and 30 agents should use S_{small} . In this agents-to-road distribution no agent could increase his own utility by deviating. The equilibrium utility sum of all agents would be 210.00. For the first best solution 67 agents should use S_{big} and 33 agents should use S_{small} , so the social welfare optimal maximised utility sum of 211.05 could be reached.

4.2 Basic model

Beginning with the simplest situation, the decision between S_{small} and S_{big} , the agents show an interesting behaviour, see figure 3.

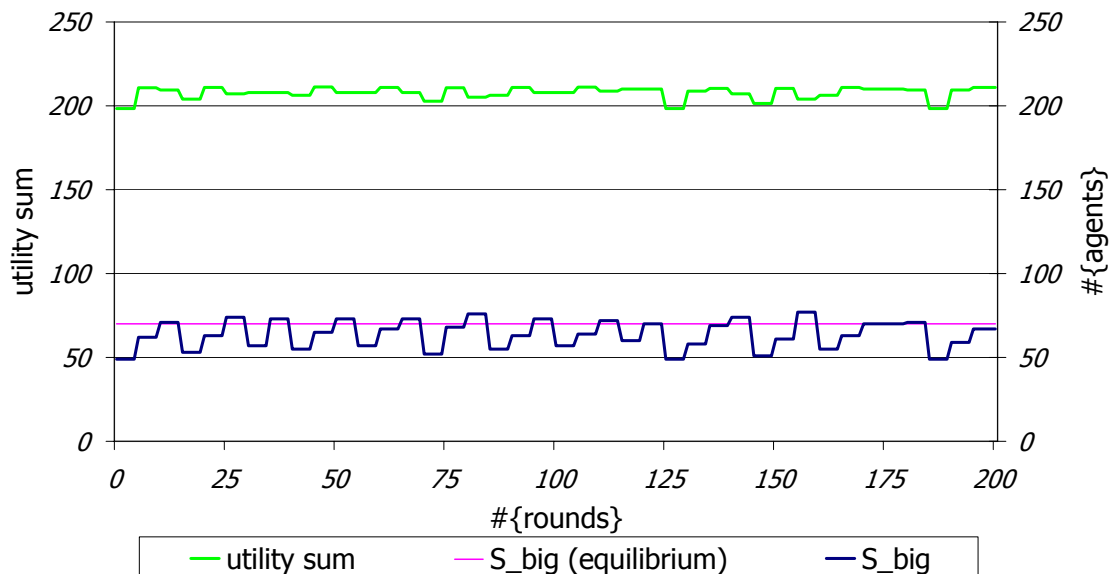


Figure 3: simulation results, basic model

The equilibrium number of agents on S_{big} should be 70. Notice that in this equilibrium the realised utilities of agents using S_{big} respective S_{small} are exact equal, but no agent could increase his own utility by deviating.

Several runs of the simulation show an average utilisation of S_{big} of 64, which is lower than the equilibrium. The resulting mean utility sum is about 207.73, which is significantly lower than the equilibrium utility sum of 210.00, and has a variance of 0.066613. This variance is due to a huge fluctuation on the roads within a run of the simulation, sometimes even less than 50 agents are on S_{big} , but the following analysis will only consider the averages of several runs.

The explanation for this finding lies in the functioning of the genetic algorithm. Even if the equilibrium distribution of agents on the roads is reached, there is always some cross-over-mutation which destabilises the equilibrium in the long term. Additionally, it is unlikely that this equilibrium is reached even in the short term. There is always a mutation of the agents on the relatively full road and relatively low utility, even in the case of being close to the equilibrium on S_{big} . Either they win or lose. The losers will always run through the genetic algorithm with a hundred percent chance.

Consider the case when there is less than the equilibrium number of 70 agents on S_{big} . They will enjoy a higher utility and therefore their fitness function will be higher than the ones of the agents on the relatively crowded S_{small} . A smaller portion of the agents (the

number on S_{small}) will mutate and, despite the fact of some cross-over mutation, will change to users of S_{big} – not many. As highly likely result, more than 70 agents will use S_{big} now. In the case of a larger than equilibrium number of users of S_{big} , they will get the lower utility and therefore will mutate. There is a great number of agents possibly switching back to S_{small} and so there is again a relatively large group of agents on S_{small} .

Empirical evidence of such a back switching behaviour is given by a study of Tacken and de Boer (1989, 1991). An improvement in the beltway around Amsterdam created a change in people’s driving behaviours and ‘traditional’ congestion places become less used which results in less congestion. After this happened, people began to switch back to ‘traditional’ behaviours again.

In our simulation similar results are obtained using an exponential utility function instead of our specified linear function, which is why we stick to the simpler linear function.

4.3 Basic model extended by ATIS

Now we introduce the traffic radio. Since there is almost no significant difference in results between the quality of the traffic radio and the results, we pick two arbitrary values for the traffic radio update interval: 20 and 1, the latter one is the reference case for a perfect traffic radio.

Starting with the former case, the variance of the agents' utility decreases and the mean utility increases significantly, a typical simulation run is presented in figure 4:

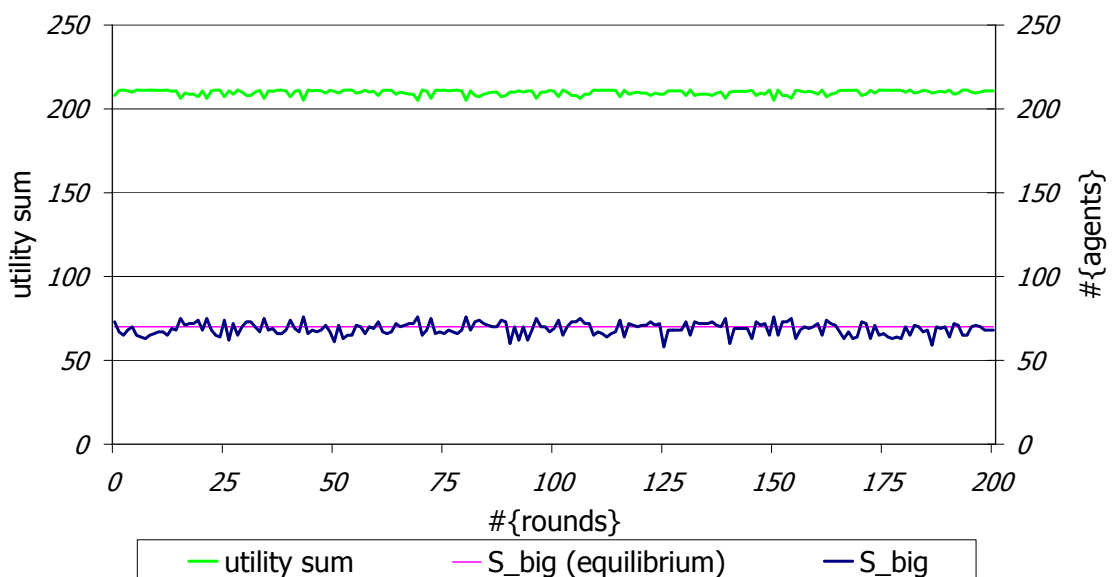


figure 4: route choice, model with ATIS, interval = 20

The mean utility sum is now about 209.81 with a variance of 0.008558. Compared to the simulations without ATIS the mean utility sum has increased and the variance decreased. This

happened because the number of agents on the road is now much closer to the equilibrium distribution in every round. Now, between 40 and 60 per cent will consider the traffic radio in their decision – either by direct or contrarian response and the ratio between direct and contrarian response is a little above 2 / 1, see figure 5:

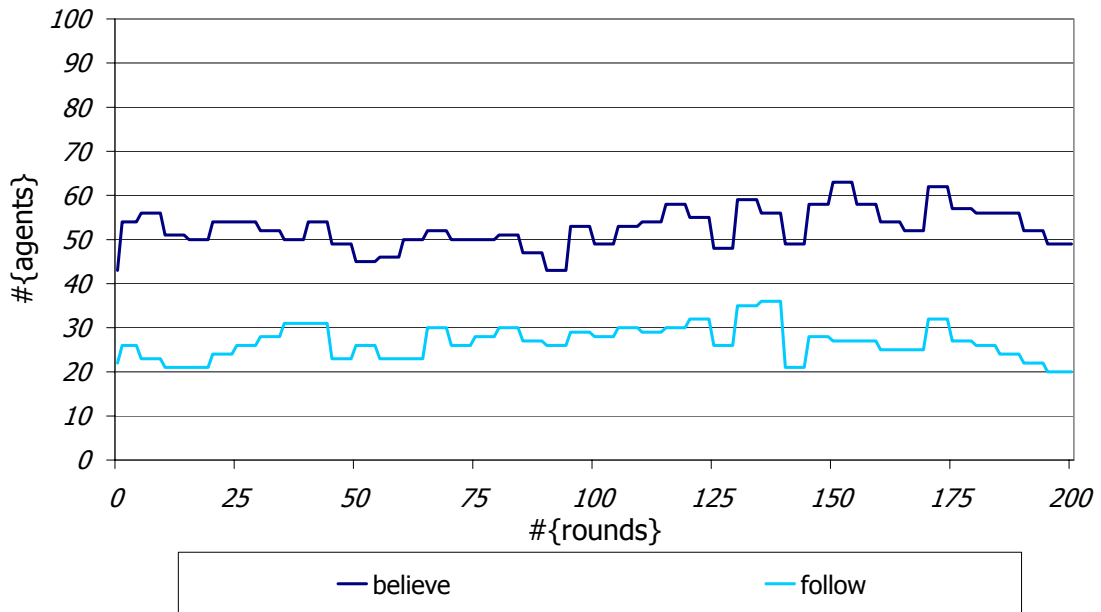


Figure 5: reaction to ATIS, model with ATIS, interval = 20

In the case of a perfect traffic radio where the update interval is 1 the mean utility sum goes on increasing to 210.09 and the variance decreases to 0.001651. However, no serious change in agents' behaviour is observable.

Finally, the average utility increases in both cases in comparison to the case without traffic radio, but the agents' utility still varies a lot within a simulation.

So why does not every agent follow the traffic radio directly, because this would lead the agents to the equilibrium?

It's again the genetic algorithm in combination with the model's implementation. When the genes force the agent's behaviour to the region of the equilibrium, much of the outcome is determined by chance. For some there is no need to consider the traffic radio if there is a group large enough who does – their concern will create a sort of “public good”, they compensate for the agents who ignore the traffic radio and even for the agents who choose the contrarian response, because these agents are outnumbered by the factor 2, as mentioned above. This leads to the quite unstable outcome, for instance, there should not be any contrarian responses in the case of a perfect traffic radio. A simulation with disabled

contrarian response node is welfare enhancing for average utility and its variance will be significantly better.²

A simple³ OLS regression supports our explanation, see figure 6:

$$AVG_U_i = \beta_0 + \beta_1 * AVG_n_Believe_i + \beta_2 * AVG_n_dont_Follow_i + \varepsilon_i$$

Model 1: OLS estimates using the 39 observations 1-39

Dependent variable: AVG_U

<i>VARIABLE</i>	<i>COEFFICIENT</i>	<i>STD.DEV.</i>	<i>T-STAT</i>	<i>2Prob(t > T)</i>
0) <i>const</i>	83,1481	0,664550	125,119	< 0,00001 ***
11) <i>n_Believe</i>	0,0167860	0,00800095	2,098	0,042987 **
10) <i>n_dont_Follow</i>	-0,0405304	0,0127177	-3,187	0,002970 ***

unadjusted R² = 0,22322

F-statistic (2, 36) = 5,17259 (p-value = 0,0106)

Figure 6

For interpretation: the more agents minded the traffic radio in a simulation run, the higher the average utility, as shown by the positive coefficient of “Believe”. The average utility decreases, the higher the number of agents who respond in a contrarian way.

In the end one finds that the genetic algorithm works fine to embrace the equilibrium. But because of the special circumstances mentioned above it still leaves room for some marginal opportunity to improve welfare by an ATIS, here the traffic radio.

5 Conclusions

This paper examines the effect of ATIS on commuter behaviour. Our simulation shows that introduction of ATIS in form of traffic radio leads to significantly higher utility with lower variance. It is interesting that our simulations have shown that not every agent will follow the recommendation directly to achieve this effect. Another – slightly surprising – result is that there are still agents who respond in a contrarian way.

Further research should focus on how to set incentives for drivers to believe and follow ATIS. As every driver who does not follow the recommendation has an external effect on the others’ utilities, it should be tried to make them for this effect reliable. A Vickrey-Clarke-Groves mechanism (Vickrey (1961), Clarke (1971), Groves (1973)) could be used for that purpose, but a problem may occur, as not every individual’s behaviour could be observed.

² Further results are available from the authors on request.

³ Since each simulation run is a random draw of the same data generating process, OLS should be applicable. Simulation parameters are: traffic radio update interval 20 and the static linear utility function.

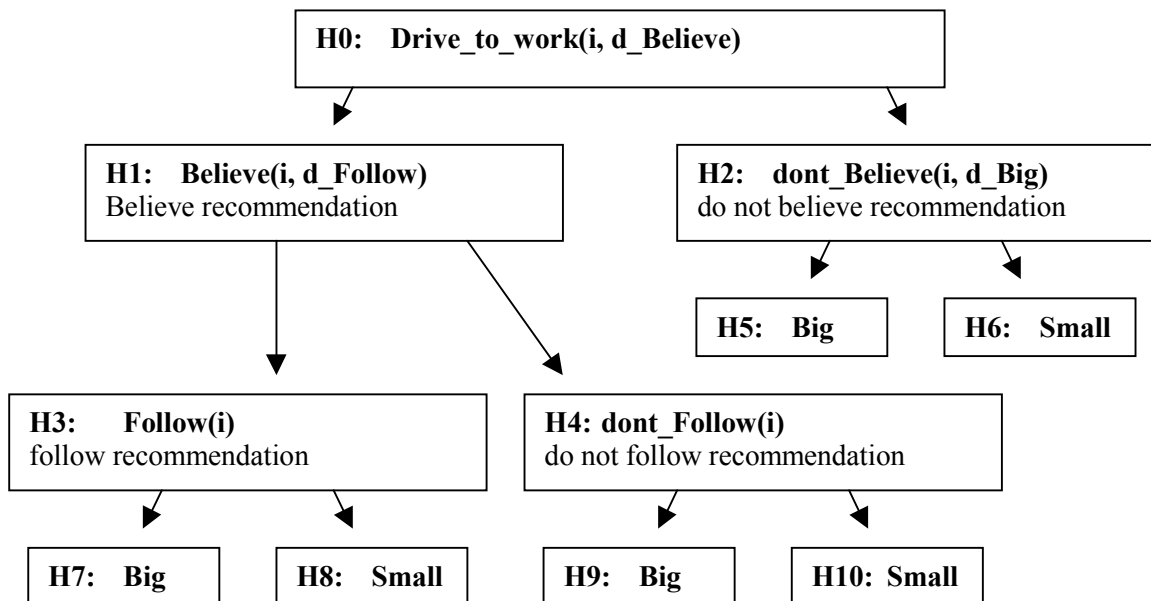
Another direction for further research could be using of genetic algorithm on more complex travel behaviour models, like Hivert's (1997) SATCHMO framework or like the Prism-Constrained Activity-Travel Simulator described by Kitamura et al. (1996).

6 Appendix: Specifications

6.1 Parameters, variables and constants of the decision tree

<code>S_big</code>	constant for big road
<code>S_small</code>	constant for small road
<code>S_neutral</code>	constant for no road
<code>n_activated</code>	number of agents, already activated in actual round
<code>n_Big, n_Small</code>	number of agents on the roads
<code>E_interval</code>	interval of actualisation of route recommendation (for no recommendations set $E_interval > \text{number of agents}$)
<code>Recommendation</code>	route recommendation, possible values: <code>S_big</code> , <code>S_small</code> , <code>S_neutral</code>

6.2 Decision tree



6.3 Nodes

For node specifications, nodes are specified as done by Pitz (2005)

T:	Name of Node and his leafs
C:	exogenous condition for activating this node
R:	results: modifications of variables
A:	modifications on gene's fitness

Node specifications are:

H0:	Drive to work(i, d Believe)
T:	Drive_to_work ([i, d_Believe]:[i: ½]) \prec_{by} H1(i, d_Follow) \otimes H2(i, d_Big)
C:	-
R:	on_activated=n_activated+1 if n_activated mod E_interval = 0, then update recommendation oRecommendation=S_big, if utility U_big > U_small, else oRecommendation=S_small
A:	$\alpha\phi(c(i, d_Believe)) = \phi(c(i, d_Believe)) + u(i)$

H1:	Believe(i, d Follow)
T:	Believe([i, d_Follow]:[i: ½]) \prec_{by} H3(i) \otimes H4(i)
C:	Recommendation \diamond S_neutral
R:	-
A:	$\alpha\phi(c(i, d_Follow)) = \phi(c(i, d_Follow)) + u(i)$

H2:	dont Believe(i, d Big)
T:	dont Believe([i, d_Big]:[i: ½]) \prec_{by} H5(i) \otimes H6(i)
C:	-
R:	-
A:	$\alpha\phi(c(i, d_Big)) = \phi(c(i, d_Big)) + u(i)$

H3:	Follow(i)
T:	Follow([i]:[i]) \prec_{by} H7(i) \otimes H8(i)
C:	-
R:	-
A:	-

H4:	dont Follow(i)
T:	dont Follow([i]:[i]) \prec_{by} H9(i) \otimes H10(i)
C:	-
R:	-
A:	-

H5:	Big(i)
T:	Big([i]:[i])
C:	-
R:	on_Big=n_Big+1
A:	-

H6:	Small(i)
T:	Small([i]:[i])
C:	-
R:	on Small=n Small+1
A:	-

H7:	Big(i)
T:	Big([i]:[i])
C:	Recommendation = S big
R:	on Big=n Big+1
A:	-

H8:	Small(i)
T:	Small([i]:[i])
C:	Recommendation = S small
R:	on Small=n Small+1
A:	-

H9:	Big(i)
T:	Big([i]:[i])
C:	Recommendation = S small
R:	on Big=n Big+1
A:	-

H10:	Small(i)
T:	Small([i]:[i])
C:	Recommendation = S big
R:	on Small=n Small+1
A:	-

7 References

BVBW, Bundesministerium für Verkehr, Bau- und Wohnungswesen (2001):
 „Auswirkungen neuer Informations- und Kommunikationstechniken auf Verkehrsaufkommen
 und innovative Arbeitsplätze im Verkehrsbereich“, internet, www.bmvbw.de (German).

Clarke, E. (1971):
 “Multipart Pricing of Public Goods”
 Public Choice, 2, 19-33.

Groves, T. (1973):
 “Incentives in Teams”
 Econometrica, 41, 617-631.

Hivert, L. (1997):
 “SATCHMO: a knowledge-based system for mode-choice modelling”
 in: Understanding Travel Behaviour in an Era of Change (P. R. Stopher and M. Lee-Gosselin,
 eds.) pp. 351-379, Pergamon, Oxford.

Kitamura, R.; Fujii, S.; Otsuka, Y. (1996):

“An analysis of induced travel demand using a production model system of daily activity and travel which incorporates time-space constraints”

Paper presented at the 5th world congress of the Regional Science Association International. Tokyo.

Kwan, M.-P.; Golledge, R. G.; Speigle, J. (1998):

„Information Representation for Driver Decisions Support Systems“

in: Theoretical Foundations of Travel Choice Modeling (Gärling, T.; Laitila, T.; Westin, K.; eds.) pp. 281-303, Pergamon.

Mahmassani, H. S.; Gregory S.; Caplice, C. G. (1997):

“Daily Variation of Trip Chaining, Scheduling, and Path Selection Behaviour of Work Commuters”

in: Understanding Travel Behaviour in an Era of Change (P. R. Stopher and M. Lee-Gosselin, eds.) pp. 351-379, Pergamon, Oxford.

NTSC, National Science and Technology Council (1999):

“National Transportation Science and Technology Strateg”

Committee on Technology, Subcommittee on Transportation Research and Development, <http://www.volpe.dot.gov/infosrc/strtplns/nstc/strategy99/index.html>.

Pitz, T. (2005)

“Genetische Handlungsbäume“

working paper, university of Bonn, Germany (in German).

Selten, R.; Schreckenberg, M.; Pitz, T.; Chmura, T.; Kube, S. (2005):

“Commuters Route Choice-Behaviours“

Games and Economic Behaviour (resubmitted).

Stern, E. (1998):

„Travel Choice in Congestions: Modeling and Research Needs“

in: Theoretical Foundations of Travel Choice Modeling (Gärling, T.; Laitila, T.; Westin, K.; eds.) pp. 173-199, Pergamon.

Tacken, M.; de Boer, E. (1989):

“Flexitime and the spread of traffic peak hour. An analysis of conditions and behaviour”

unpublished manuscript, OSPA, Delft University of Technology, Delft, The Netherlands (in Dutch).

Tacken, M.; de Boer, E. (1991):

“Change in spread of travel and working times due to opening of the Amsterdam Orbital Motorway”

unpublished manuscript, OSPA, Delft University of Technology, Delft, The Netherlands (in Dutch).

Vickrey, W. (1961):

“Counterspeculation, Auctions, and Competitive Sealed Tenders”

Journal of Finance, 16, 8-37.