

# Agent-based simulation of route switching behavior with different types of information provision

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**Abstract—** This paper presents a framework for simulation of route switching behavior within the MATSim project. The framework focuses on within-day replanning under different forms of information provision. Three major building blocks are presented, each of which represents specific aspects of driver behavior. These components comprise (i) the provision of descriptive information in the form of link travel costs, (ii) prescriptive information in the form of routes, and (iii) a model of driver satisfaction. An exemplary implementation is presented where driver perception is constrained to link traversal costs and decisions are made by application of a standard shortest path algorithm. The satisfaction of a traveler is modeled with a scoring (utility) function that evaluates routes as well as activities travelers are aiming at. The model's functionality is tested with a simple fictive network and a real-world network of Greater Berlin.

## I. INTRODUCTION

In the field of transport planning, engineers agree that the problems of transportation are no more a matter of extending the infrastructure with concrete and steel, but rather a matter of the efficient use of existing transport networks [9]. Advanced Traveler Information Systems (ATIS) are intended to fill in here by providing accurate information through a variety of devices.

An important aspect is the response of drivers to provided information. Since deployment of ATIS technologies is still in an early state, practical experiences are limited. To gain more insights into travelers' decision making in-laboratory experiments such as FASTCARS ([1] and [2]) and IGOR [3] have been proposed.

Behavioral models derived from the results of these laboratory experiments can be used in large-scale simulations to evaluate ATIS technologies. Travel time savings have been observed in several studies ([10], [11], [12] and [13]), varying from three to 30 percent depending on market penetration and network topology. Beside the lowering of travel time itself, the reduction of its uncertainty deserves to receive just as much attention.

As a contribution to research in this field, this paper presents a basic framework that enhances the MATSim system ("Multi-Agent Transport Simulation Toolkit", [www.matsim.org](http://www.matsim.org)) by capabilities of en-route and within-day-re-planning. The framework is integrated in the so-called „mental layer" of agent behavior and defines a set of interfaces in which specific implementations can model specific behavioral patterns. More specifically, the behavior of an agent is represented by modules, each of which reflects a certain behavioral aspect. The modularity allows to easily

exchange certain building blocks or even complete behavioral implementations and thus to compare and evaluate different models.

The framework allows to model ATIS strategies, corresponding driver reactions, and finally to analyze the interaction between ATIS, drivers and traffic conditions.

The remainder of this article is organized as follows: In section II the model and its conceptual background are presented. Section III describes an exemplary implementation and section IV verifies the model by means of two sensitivity studies. The paper closes with a discussion of the results of section IV.

## II. MODEL DESCRIPTION

### A. Basic agent model

In MATSim, agents follow a predefined activity plan. A plan consists of a sequence of activities, which are linked by legs (trips). A leg holds several attributes describing the travel from one activity to another such as departure time, expected arrival time, route and transportation mode. Activities contain type attributes such as *home*, *work*, *education*, *leisure* as well as further information regarding activity timing.

The behavior of an agent is fully determined through its plan. Thus, altering an agent's behavior is possible only by modification of its plan. This also implies that the modeling aspects are limited by the plan's degrees of freedom, primarily activity, departure time and route choice. The presented framework concentrates on route choice.

### B. Agent brain

Presented so far, agent behavior is constrained to execution of a predefined activity plan. In order to alter its behavior it needs to become intelligent. Intelligence is provided to the agent by equipping it with a *brain*. The essential task of a brain is to do on the fly modification to the plan. Additionally, the brain is able to determine the agent's desire to replan at all.

An agent brain comprises three further components, each of which represents a certain aspect of the replanning process. Descriptive information in the form of link travel costs are provided by a so called *link cost provider*, prescriptive information in the form of predefined routes are obtained from a *route provider* and the agent's satisfaction is modeled by the *contentment module*. However, the ways in which these three components are combined are up to a concrete implementation of an agent brain. For example, a

rational and strictly utility maximizing brain may use a shortest path algorithm as *route provider* supplied with link costs obtained from an arbitrary *link cost provider*. Figure 1 provides an overview.

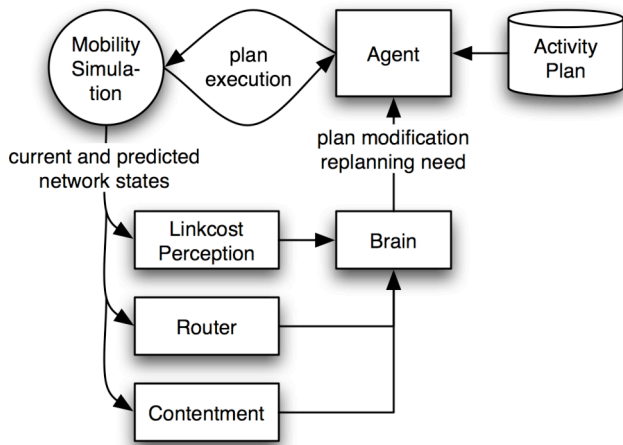


Fig. 1. Conceptual agent layout. An agent is feed with in initial activity plan. The plan can be modified by the brain with the help of a link cost provider, router and contentment module. The mobility simulation moves the agent through the network according to its plan.

### C. Types of information provision

As mentioned above the *link cost provider* and the *route provider* represent two types of information sources. From the conceptual side one can distinguish between intrinsic and extrinsic provision. However, technically these sources of information are dealt with in a unified way.

An intrinsic *link cost provider* may represent the agent's observation (what it can see by looking out of the window) or the historical knowledge an agent accumulated in previous trips. An extrinsic *link cost provider* may represent an in-vehicle device, which supplies the driver with travel times or messages broadcasted via radio.

For *route providers* this differentiation is not as distinct as above. One may imagine an intrinsic *route provider* as a representation of the process of acquiring a route when the agent thinks for itself. The extrinsic counterpart may be an in-vehicle navigation device, internet-based services, variable destination signs (VDS) or even static guide posts.

The simulation framework currently provides three different types of basic link travel time information.

*Historical* travel times represent the „typical“ state of the traffic network<sup>1</sup> as expected by the traveler, *reactive* travel times (in literature also referred as naïve or instantaneous travel times) represent a current snapshot of the traffic network and *predictive* travel times represent a forecast of the traffic state within a given time window.<sup>2</sup>

<sup>1</sup> Historical travel times are generated by running an assignment without replanning. The plans have undergone several iterations in the MATSim demand modeling framework, thus representing a network state near user equilibrium.

<sup>2</sup> Such a prediction is generated in a rolling-horizon manner by running the mobility simulation forward without re-planning and then switching back to the previously marked state.

Depending on the type of link travel costs that are supposed to be modeled, an implementation of a *link cost provider* may compose the three basic types to a new representation of link costs. Of course *link cost providers* are not restricted to the information generated by the mobility simulation. Static information may be read out of files or generated by other modules a priori. It would be even conceivable that a *link cost provider* operates its own sub-simulation to generate specific information.

## III. EXEMPLARY IMPLEMENTATION

This section presents an exemplary implementation which models agent behavior in terms of bounded rationality. The model makes the following two assumptions: (i) The agent is strictly utility maximizing considering the information he possesses. (ii) However, its available information is based on individual observations and estimation of its surroundings and thus is limited by the extent of its perceptivity.

The re-planning mechanism as it is processed by the agent brain can be separated in three quite typical steps [15]:

1. Perception. The agent observes its current environment which basically is given by the current traffic state.
2. Deliberation. The agent searches a new route based on this information.
3. Execution. The agent modifies its plan so that the mobility simulation will move it through the network according to its new route.

### A. Link cost perception

An agent has two ways to acquire information: It can observe its direct surroundings and it can estimate information that cannot directly be perceived. Estimation is based on current observation in combination with historical and common knowledge. Observations are based on the current state of the traffic network but are distorted by individual errors of perception. Consequently, to model the driver's perception and estimation of link travel times the *historical* and *reactive* travel times are required.

Observations are spatially limited to the agent's current link and on its immediately succeeding links (i.e. all outgoing links of its downstream node). For these links the agent is aware of the reactive (instantaneous) travel times. However, the agent's perception is distorted by two individual perception errors. The first is a white noise added to the reactive travel times and the second represents the uncertainty of appraising the correct travel time when the current traffic state differs from the habitual known:

$$c^* = c^r + \varepsilon_1 + \varepsilon_2 \quad (1)$$

with  $c^*$  the perceived travel time,  $c^r$  the reactive travel time,  $\varepsilon_1$  and  $\varepsilon_2$  the perception errors. The error  $\varepsilon_1$  is a standard normally distributed random variable with variance proportional to the reactive travel time,

$$\varepsilon_1 \sim N\left(0, \delta^2 = k_1 c^r\right), \quad (2)$$

with  $k_1$  a scaling parameter. The second perception error becomes noticeable when the observed traffic state differs from the one the agent is used to. If, e.g., link travel times are twice as high as historically observed, an agent is more unsure about the real travel time than if observations match its historical knowledge. The resulting error,  $\varepsilon_2$ , again is a standard normally distributed random variable but now with variance dependent on the deviation between the current randomized traffic state to the historical:

$$\varepsilon_2 \sim N\left(0, \delta^2 = k_2 \left| \frac{c^r + \varepsilon_1}{c^h} - 1 \right| \right) \quad (3)$$

with  $k_2$  a scaling parameter.

For the estimation of travel times on unobservable links the agent compares the perceived reactive travel time on his current link and the travel time of his historical knowledge.

$$c'_i = \frac{c^*}{c^h} c_i^h \quad (4)$$

with  $c'_i$  the estimated travel time on link  $i$ ,  $c^*$  the perceived reactive travel time on the current link,  $c^h$  the historical travel time on the current link and  $c_i^h$  the historical travel time on link  $i$ . This is a simple linear extrapolation of the historically learned travel times. Additionally, estimated and perceived link travel times are corrected if they fall below the free flow travel time.

### B. Routing

The routing is done with a time variant Dijkstra best path algorithm. The routing algorithm is supplied with link travel costs by a link cost provider as described in the previous section A.

In the literature, route choice models are often realized as random utility models that represent the human non-deterministic behavior [14]. Since MATSim focuses on large-scale scenarios, the generation of choice sets as required for discrete choice models is too expensive in terms of computational performance. Thus we choose a purely simulation-based approach, apply strict shortest path algorithms, and realize the non-deterministic behavior by randomization of link costs as described in the previous section.

### C. Contentment

Our exemplary implementation of the agent brain uses a *contentment module* to determine the agent's need to replan. Contentment is represented as a scalar value out of the interval  $[-1,1]$ , where 1 means the agent is pleased, 0 the agent is indifferent, and -1 the agent is displeased. As an agent becomes displeased (i.e. values less than 0), its need to replan increases. Due to limits in computational

performance, agents do not decide to replan themselves. Replanning is always controlled and invoked by the simulation. The probability that an agent is requested to replan increases with his need to replan. One could say the simulation controller concentrates the computational resources it invests in replanning on displeased agents.

This simulation logic might appear to be at odds with its very own modelling assumptions since a traveller that does feel the need to replan would definitely do so in the real world. However, to get a simulation that is practical for real-world applications one sometimes has to forego a certain degree of realism.

The implementation for the *contentment module* used here is based on a scalar scoring (utility) function for plans introduced by Charypar and Nagel in [4]. This scoring function evaluates the quality of a plan by summing the utilities of all activities that are performed and all travel (dis)utilities. Since the model presented in this article deals with within-day-replanning, only an agent's current route and the succeeding activity are of interest. Therefore, we determine the utility of the succeeding activity and the (dis)utility of being late.

$$U = U_{act} + U_{late} \quad (5)$$

Departure time choice is not considered here.

The utility for performing an activity is a logarithmic function

$$U_{act}(t_{dur}) = \beta_{dur} t^* \ln \frac{t_{dur}}{t_0} \quad (6)$$

with  $t_{dur}$  the expected duration of the activity,  $\beta_{dur}$  the value-of-time for performing an activity,  $t^*$  the scheduled duration of the activity (as defined in the plan) and  $t_0$  the duration at which the utility starts to be positive.

The penalty, or more precisely the negative utility for being late is modeled as

$$U_{late} = \begin{cases} \beta_{late} (t_{arr}^* - t_{arr}) & \text{if } t_{arr}^* < t_{arr} \\ 0 & \text{else} \end{cases} \quad (7)$$

with  $\beta_{late}$  the value-of-time for being late,  $t_{arr}^*$  the scheduled arrival time (as defined in the plan), and  $t_{arr}$  the expected arrival time. We can now define  $t_{late} = t_{arr} - t_{arr}^*$  and  $t_{dur} = t^* - t_{late}$ , thus (6) and (7) are dependent on  $t_{late}$ . If an agent is late, beside  $U_{late}$  he is also penalized by gaining less utility for  $U_{act}$ .

The contentment of an agent is defined as

$$c = k \left( \frac{U}{U^*} - 1 \right) \quad (8)$$

with  $c$  the contentment,  $k$  an attenuation factor,  $U$  the expected utility, and  $U^*$  the utility when maintaining the plan.<sup>3</sup> The attenuation factor  $k$  causes agents to replan less frequent if they are close to their destination. This behavior has been observed in [5] and [6]. The attenuation factor is determined by

$$k = 1 - e^{-\frac{\mu}{L}l} \quad (9)$$

with  $\mu$  a scaling parameter,  $L$  the length of the complete route and  $l$  the distance the agent still has to travel.

#### IV. SIMULATION RESULTS

##### A. Introduction

With the above implementation, two scenarios were run which will be described in the following: first a synthetic corridor example (called the “simple” scenario), and then a scenario based on real-world data from Berlin (called the “Berlin” scenario). For both scenarios, the set-up is as follows:

- As base case, a set of initial plans is given. Plans contain departure times and routes for every agent.
- These plans are then run through the simulation described in this paper. Repeated runs are done, where the replanning probability is incremented in small steps. Agents replan at each intersection with this certain replanning probability. In case of presence of the contentment module the replanning probability is weighted with the agent’s need to replan.

For the “simple” scenario, the initial plans are manually constructed. For the “Berlin” scenario, they are taken from the MATSIM “demandmodeling” version, which for the purposes of the paper here can be described as a dynamic traffic assignment. The plans for the “Berlin” scenario can be considered “relaxed” (i.e. close to a Nash equilibrium) with respect to the MATSIM “demandmodeling” version, but they are in general not relaxed (i.e. out of Nash equilibrium) with respect to the simulation discussed in the present paper (since it uses a different traffic flow model).

##### B. “Simple” test scenario

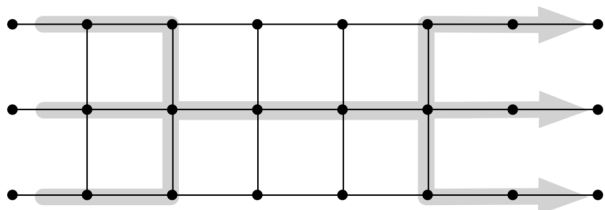


Fig. 2. Simple test network. The gray arrows denote the routes as defined in the initial plans. Agents depart at the six leftmost horizontal links and travel via the middle route to the three rightmost links.

We first set up a simple test scenario with a grid shaped

<sup>3</sup>  $U^*$  is calculated a priori by scoring the initial plan.

network including 41 links. All links are equal in their attributes (1000 m length, 1800 vehicles per hour max. flow and 7.5 m/s free speed). The demand consists of 6000 agents departing at 7:00 and traveling from the left to the right side (see fig. 2).

According to their initial plans, all agents use the middle route. Because of its limited capacity, spillback occurs shortly behind the demand entry points. The resulting travel times are used as the historical traffic pattern. It is questionable if this is realistic, since the historical travel times are not in user equilibrium. However, this extreme case shows more clearly the effects of within-day-replanning.

We run several simulations with different types of *link cost providers* to investigate the impact of descriptive information provision. Beside the model of agents link travel time perception presented in III.A, we additionally provided the agents directly with historical, reactive and predictive travel times. All test runs have been done with and without the *contentment module* of III.C. The average nash equilibrium deviation without replanning is 9:50.

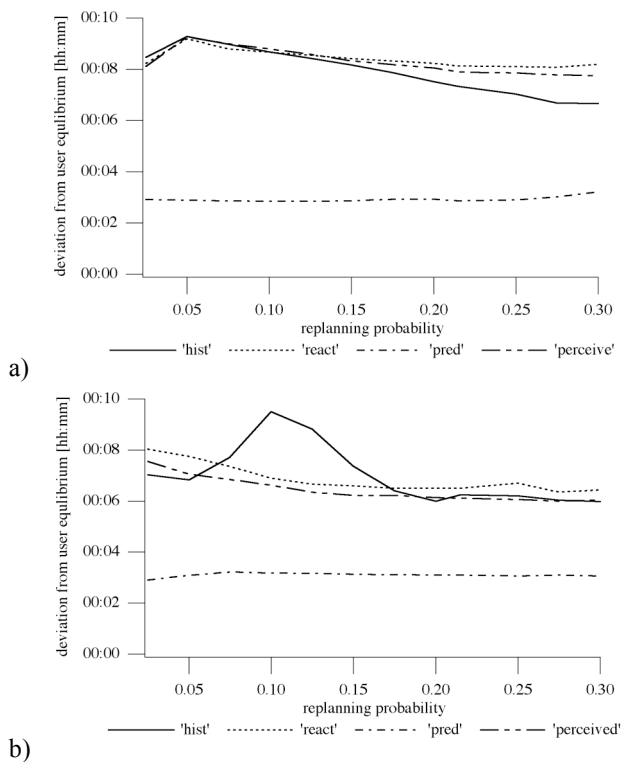


Fig. 3. Comparison of link cost provider in the simple test scenario. ‘hist’ = historical, ‘react’ = reactive, ‘pred’ = predictive (with 30 mins prediction window) and ‘perceived’ = perceived travel times. a) without contentment module, b) with contentment module

Figure 3 shows results that one may not expect at first glance. Predictive information provision leads to less deviation from a user optimum than reactive information provision. But replanning with historical travel times leads to better results than with reactive (instantaneous) travel times. The *link cost provider* which models the agent’s

perception produces results that are between the ones of the historical and the reactive *link cost provider*. As explained in III.A it uses the historical and reactive information with two random errors.

The results with reactive information provision demonstrate the problem of overreaction. Overreaction describes the situation in which drivers overcompensate in response to information, again causing sub-optimal traffic conditions. This effect can be well observed with high replanning probabilities.

Considering the runs with the *contentment module*, one can see that at least for the historical, reactive and perceived link travel times we achieve the expected effect: Switching the *contentment module* on results in less deviation from the user optimum as without. Recall that with the *contentment module* displeased agents are replanned with a higher probability. For the run with predictive information the two curves in fig. 3a and 3b barely differ.

This also shows that the *contentment module* can be used to increase computational performance (at least for reactive and perceived travel times). For the simple test scenario it is possible to lower the replanning probability if using the *contentment module* to achieve equal results as without the *contentment module* and higher replanning probabilities. And lower replanning probabilities means that less agents are replanning which in turn improves computational performance.

However, one has to take care of choosing realistic parameters. In the real world one could say that the “thinking power” is concentrated over displeased travelers, while indifferent and happy drivers are unconcerned about their route. The equivalent to “thinking power” in the simulation is the computational power, which like in the real world can be concentrated on displeased agents. One has to find the right balance of an efficient simulation but without neglecting realistic behavior.

### C. “Berlin” test scenario

To investigate the behavior of the framework in real world applications, a large-scale scenario with a reduced road network representing the metropolitan area of Berlin (Germany) has been set up. The network includes approximately 2400 links and is bounded by the Berlin beltway (fig. 4).



Fig. 4. Reduced road network representing the metropolitan area of Berlin.

Activity plans have been generated with the MATSim “demandmodeling” package and represent a 10 percent sample of Berlin’s population (approx. 170,000 agents).

The same investigations as with the simple test scenario have been conducted for the Berlin scenario. The average nash equilibrium deviation without replanning is 5:06.

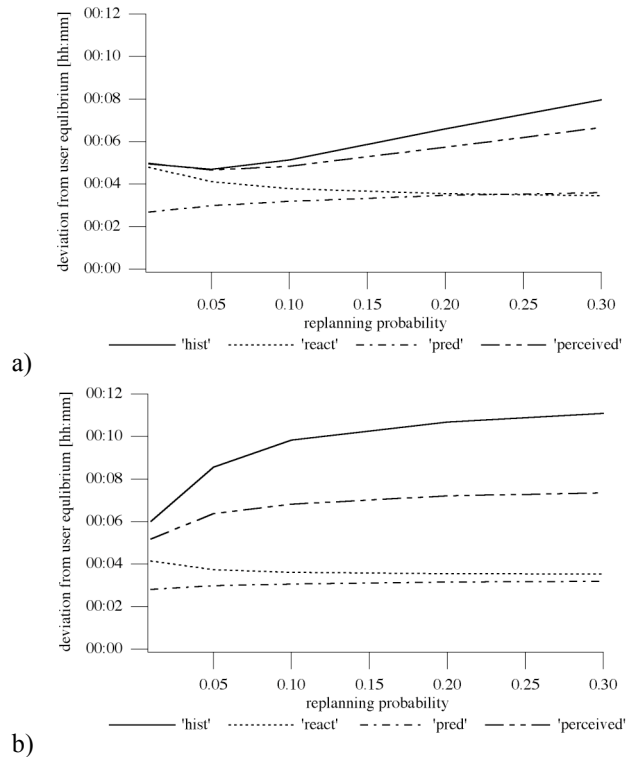


Fig. 5. Comparison of link cost provider in the Berlin test scenario. ‘hist’ = historical, ‘react’ = reactive, ‘pred’ = predictive (with 30 mins prediction window) and ‘perceived’ = perceived travel times. a) without contentment module, b) with contentment module.

On qualitative inspection of fig. 5 we now observe the expected results: Better information leads to better results (“predictive” < “reactive” < “perceived” < “historical”). The phenomenon of overreaction with reactive information provision does not occur in this scenario.

But in contrast to the simple scenario, increasing the replanning probability does not always improve results. With the use of historical or perceived travel times it even dramatically impairs results. Recall that the initial plans for the Berlin scenario have undergone several iterations in the MATSim “demandmodeling” framework and are thus close to the user equilibrium. Accordingly, it is not possible to further improve the traffic state by providing additional information to drivers. Even the improvements with reactive travel times are small.

The *contentment module* again amplifies the effects of information provision. With the use of historical or perceived travel times the contentment module clearly impairs the results. Regarding the reactive and predictive *link cost provider* values are nearly the same as without the



*contentment module.*

Considering the results of the predictive information provider, the increasing values of user equilibrium deviation seem to be related to the accuracy of the prediction. For remembrance, the prediction is done by running the simulation forward without replanning. It is obvious that if more agents are allowed to replan, the experienced traffic state potentially differs more from the prediction as if fewer agents are allowed to re-plan.

However, this behavior has not been observed in the simple test case. One explanation could be: The range of possible trip durations is quickly reduced in the simple test network, since the routes do not differ that much (actually, there are only three main routes). Thus if several agents re-plan, the chance that the experienced traffic state and the prediction diverge is still low. In contrast, the large Berlin network is less constrained and consequently the probability of divergence is higher.

## V. CONCLUSION

This work presented an agent-based model that describes the route switching behavior of travelers. The model distinguishes between a module for link cost perception, route searching and contentment. Together, these modules represent an agent's behavior. The model provides flexible options for adjusting the behavior by choosing different implementations of the modules. For the studies presented here, Dijkstra's best path-algorithm has been used for the route searching model, a scoring function to model the contentment, and historical, reactive, predictive travel times as well as combinations of them to model the perception of link costs. Beside the exemplary implementation, additional implementations modeling simple activity choice [7] and guidance by means of variable message signs [8] exist in the MATSim framework.

The sensitivity studies showed that the results are not always as one at first glance would expect. In the simple test scenario we had to deal with the phenomenon of overreaction, whereas the contentment module showed the expected effect. In the Berlin scenario, better information provision lead to better performance of drivers, but compared to the run without replanning (nash equilibrium deviation 5:06) only the reactive and predictive information proved to be advantageous. Also the contentment module proved to be counterproductive.

Altogether, it can be expected that the presented framework – once it has been validated and parameter calibration has been undertaken – provides valuable insights into the effects of ITS measures not only in current and future traffic conditions, but also on driver contentment itself.

Our future research will concentrate on the impacts of the driver's satisfaction on route choice and also the decision making process considering travel time uncertainty and risk aversion. In this context it will be practicable to also deal with departure time choice which has been neglected in our

early studies.

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