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Exceptional Events in a Transport Simulation

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Abstract. Today, typical techniques in the field of transport planning are designed to analyze scenarios which describe common situations like an ordinary working day without remarkable incidents. A scenario containing exceptional events that occur by chance, increases the complexity of the required model significantly.

A short introduction into a traditional methodology as well as some commonly used techniques is given. Moreover, the benefits of modern approaches are highlighted. MATSim, a multi-agent traffic flow simulation which implements those new techniques, is presented.

It is highlighted why both—the traditional methodology as well as the agent-based simulation approach—will fail for scenarios with unexpected events. An improvement of the simulation approach is presented, which overcomes these problems and, therefore, is an appropriate instrument for such scenarios.

Contents

1 Introduction

In recent years, micro-simulation has become very important in the fields of traffic simulation, traffic analysis and traffic forecasting. Compared to conventional models, advantages are the possibility to explicitly model the decision making process of each individual and a very wide range of outputs like group specifical statistics or information about single travelers in the simulation.

People do not just produce traffic because they like to do so, in fact they have desires which they try to satisfy, which—in turn—results in traffic. To do so, they perform activities like *being at home*, *meeting friends* or *going to work*. For each activity, its location as well as its start and end time are specified. However, typically not all of these activities can be performed at the same location. Therefore, people have to travel from one location to another, which produces traffic. It is obvious, that a person tries to optimize his or her daily plan. In this context, a *daily plan* of a person describes all activities that this person performs on this day as well as the trips that connect those activities. For each trip, a transportation mode as well as a route is defined. To optimize a person's daily plan, the person has to make several decisions and has various options to choose from:

- *Activity choice*: Which activities do I have to perform? Which ones do I want to perform?
- *Activity duration choice*: How long can I stay with my friends?
- *Activity departure time choice*: When do I have to depart to be at work in time?
- *Activity chain choice*: Should I go shopping before or after work?
- *Location choice*: Should I go shopping to the mall or the small store in the neighborhood?
- *Mode choice*: Should I go by car or by bike?
- *Route choice*: Which route should I take to get to my friends?

All of the decisions mentioned above directly influence other parts of the daily plan. If e.g. a person decides to stay longer at home in the morning, this person has to work longer and therefore may not be able to meet friends in the evening. It is also possible, that a person is affected by an (exceptional) event like a traffic jam.

As a result, the person will be late at the next activity and has to decide how to react—for example shorten this activity or skip another one. These examples show the importance of describing the activities and trips of a person as connected schedule, where one element interacts with the others instead of using aggregated data, where only the number of trips from an origin to a destination is known.

For many common transport planning problems like “How will traffic flows evolve if a new highway is built?”, just monitoring what a person is doing is not sufficient. To be able to answer such questions, it is necessary to extrapolate from a given model. When doing so, it is important that the decision making process of the individuals is modeled. While travelers in general try to optimize their personal utility, a transport planner has to take care of the system as a whole. Therefore, it is necessary to predict how travelers perceive planning measures and how they will react to them. Clearly, understanding the decision making process of the travelers will help to do so.

For a transport planner, several information about a scenario are from interest. In this context, a *scenario* describes a simplified representation of the region of interest. It defines the area as well as the population and the road network. Typical examples for information, that are required by a transport planner, are aggregated values like time dependent traffic volumes, modal split, mean travel time and distance. However, also information that is related to single persons or groups of people are of interest. A common example is the activity chain distribution per population group (e.g. grouped by age or gender). It is obvious that only a model based on individuals can deliver all those information.

In the next section, a traditional planning methodology as well as some techniques that are commonly used today, are discussed. Subsequently, the implementation of those modern techniques into an agent-based simulation tool is described. Finally, the problem of simulating exceptional events with a simulation tool is discussed and a solution for the problem is presented.

2 The Four Step Process and its Alternatives

2.1 Four Step Process

Traditionally, the so called *four step process* has been used for transport planning [1, 2]. The aim is to determine the demand on a transportation network in terms of trips between zones within the study area. A zone is a geographical region, e.g. a municipality or a district of a city. Figure 1 shows the the four steps, which are:

- Trip generation
  In the first step, the number of trips produced in each origin zone and the number of trips attracted by each destination zone are determined. This is done using zonal specific data like the number of inhabitants or working places. Additionally, factors like the density and the capacity of the road network are taken into account.

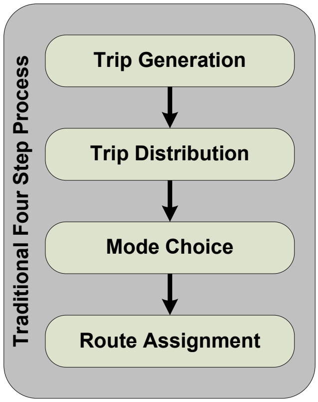

Figure 1: Traditional Four Step Process

- Trip distribution
  The task of the trip distribution is to connect origins an destinations. For each origin, the fraction of trips that goes to a specific destination is determined—and vice versa. Thus, a so called origin-destination (OD) matrix is created, which enumerates the number of trips from each origin to each destination.

- Mode choice
  In this process step, the transportation modes like driving, walking, going by bike or taking the bus, are determined for each trip. Factors like socio-economic attributes of the population or the availability of public transport are taken into account.

- Route assignment
  Finally, in the route assignment, each trip is assigned to a path on the network. Typically, a user equilibrium (UE) is targeted. In a user equilibrium, all used paths for a given origin-destination pair at a given time have the same travel costs. Moreover, there is no unused path with lower travel costs [3].

A major drawback of the *traditional four step process* is its sequential execution. Typically, the trip distribution as well as the mode choice use assumed travel times in their models. However, after conducting the route assignment, more realistic travel times are available. Therefore, the traditional structure of the process should be extended to an *iterative four step process* as shown in Figure 2. By doing so, the three steps of *trip distribution*, *mode choice* and *route assignment* can be repeated multiple times until the assumed travel times match the travel times calculated by the route assignment step.

The *four step process* is a simple and well known tool for transport planning, which produces unique and reproducible results. Even very large scenarios can be investigated with relatively small effort. However, its results are not realistic or

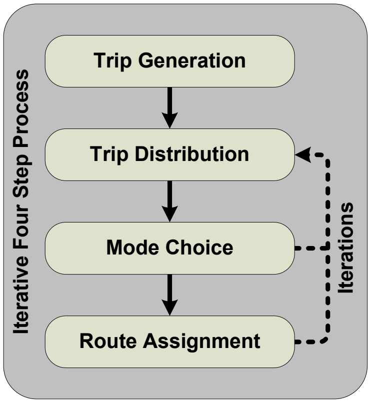

Figure 2: Iterative Four Step Process

detailed enough for many modern transport planning problems. On the one hand, the results are traffic streams which cannot be disaggregated to individual travelers. Therefore, decisions like mode or route choice cannot be made based on individual preferences of a traveler. On the other hand, temporal dynamics are not represented accurately. It is assumed, that the traffic flows are static, i.e. time independent. Thus, time dependent effects like congestion during the peak hours cannot be reproduced.

Today, the drawbacks of the *four step process* can be overcome by using methods such as *activity-based demand generation* and *dynamic traffic assignment*, which are described in the following sections.

2.2 Activity-based Demand Generation

In contrast to the *four step process*, *activity-based demand generation* models the traffic demand on an individual level. Therefore, the population within the modeled area is represented by a synthetic population which is created using e.g. census data. This synthetic population is not an exact copy of the real population, but on a statistical level (for example distribution of gender, age and household income or population density in a given region) both populations match.

In a second step, for each individual of the synthetic population, a complete daily activity schedule is created. Additionally, the location of each activity is determined based on person specific properties such as the availability of a car or the amount of money that can be spent for leisure activities. Moreover, the start and end time of each activity are contained in an activity schedule.

Finally, for each trip between two scheduled activities, a transportation mode is selected. This step is comparable to the *mode choice* of the *four step process*. However, additional demographic attributes of the individual that performs the trip can be taken into account.

Activity-based demand generation represents the first three steps of the *four step* *process*. However, instead of modeling on an aggregate level, travelers are modeled as individuals, which allows a much more detailed representation of the travel demand. Moreover, the generated travel demand is now time dependent. Therefore, the demand has to be aggregated to be used as input data for the *route assignment* approach of the *four step process*. Alternatively, a *dynamic traffic assignment* method can be used.

The concept of *activity-based demand generation* is e.g. discussed by [4] and [5], examples for its implementation are given by [6], [7] and [8].

2.3 Dynamic Traffic Assignment

A very common technique to overcome the limitations of *static traffic assignment* methods used in the *four step process* is *dynamic traffic assignment*. Instead of static flows, *dynamic traffic assignment* calculates time of day dependent link volumes. Using a time dependent demand (as e.g. created *activity-based demand generation*) and a model of traffic dynamics (e.g. a queue model), the *dynamic traffic assignment* tries to find an optimal route for every conducted trip. Basically, this is the *Nash Equilibrium* applied to a dynamic problem (see [9]).

However, the theory of *dynamic traffic assignment*, as discussed by [11], is not as well understood as *static traffic assignment* and has less mathematically proven properties. Moreover, it is not guaranteed, that there is a unique solution for every traffic assignment problem that includes congestion. [10] shows, that it is possible to find more than one *Nash Equilibrium* for a pair of an origin-destination matrix and a network.

Typically, a simulation approach is applied to solve the *dynamic traffic assignment* problem. A simple implementation of the *dynamic traffic assignment* problem contains a representation of the road network and a logic how vehicles move within the network. A common way to reach an equilibrium is an iterative approach [13,14]. Initially, routes for all trips of a given demand are calculated. Then, the (traffic flow) simulation executes those routes simultaneously. The simulation produces time dependent link travel times which can be used to improve some or all routes of the simulated population. The simulation as well as the rerouting is repeated many times until a relaxed state (e.g. a *Nash Equilibrium*) has been reached.

2.4 Combination of Activity-based Demand Generation and Dynamic Traffic Assignment

Today, *activity-based demand generation* and *dynamic traffic assignment* are often combined in a single framework. Together, they replace all steps of the *four step process*. On the one hand, they can be coupled using origin-destination matrices. Doing so theoretically results in a backwards compatibility to the *four step process*. However, *dynamic traffic assignment* requires time dependent matrices which are not directly compatible with static matrices as used in the *four step process*. This can be solved by converting between static and dynamic matrices, but some drawbacks,

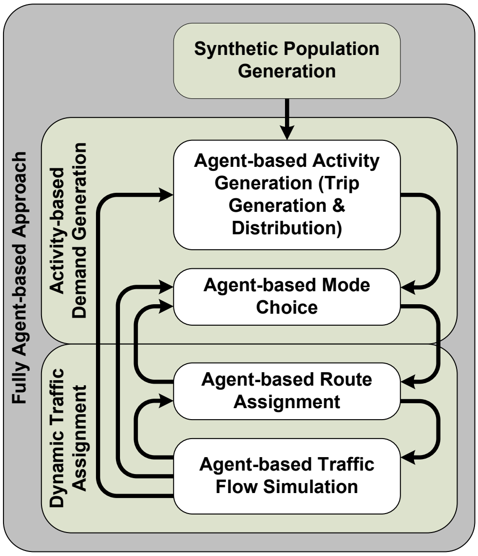

Figure 3: Fully Agent-based Combination of Activity-based Demand Generation and Dynamic Traffic Assignment

like the loss of the disaggregation to individual travelers, remain. Thus, an iterative feedback from the traffic flow simulation can only be respected on an aggregate level but not by each individual. Therefore, decisions based on an individual's attributes cannot be modeled accurately.

The drawbacks of an origin-destination matrix based approach can be overcome with a *fully agent-based approach* as shown in Figure 3. This approach directly feeds the results of the *activity-based demand generation* into the *dynamic traffic assignment*. Thus, travelers are maintained as individuals with personalized attributes during the entire process. Therefore, it is, for example, easy to implement individual route preferences. Imagine two trips from the same origin to the same destination at the same time. One agent might have a very high value of time and therefore will prefer a faster route using tolled roads. Whereas another agent might have a half-price ticket for public transport and will take the bus instead of going by car. Examples for an implementation of the combination of *activity-based demand generation* and *dynamic traffic assignment* are given by [14], [15] and [16].

3 MATSim - A Multi-agent Transport Simulation Toolkit

MATSim (Multi Agent Transport Simulation) is a framework for iterative, agent-based micro-simulation of transport systems. It is currently developed by teams at ETH Zurich and TU Berlin as well as the Senozon AG, which is a spin-off company founded by former members of both institutes. MATSim consists of several modules that can be used independently or as part of the framework. It is also possible to extend the modules or replace them with new implementations. A detailed description of the framework, its capabilities and its structure is given by [14] and [17]. Because of its agent-based approach, every person in the study area is modeled as an individual agent in the simulated scenario. Each agent has individual attributes such as age, sex, available transport modes and scheduled activities. Due to the modular structure of the simulation framework, the agent's parameter set can be easily extended by new attributes, for example a routing strategy that should be used or areas of the road network that the agent knows. The application of MATSim to a large scale scenario of Switzerland (over 6 million agents simulated on a high resolution network with 1 million links) is presented in [18].

Figure 4 shows the structure of a typical, iterative MATSim simulation run. After the creation of the initial demand, the daily plans of the agents are modified and optimized in an iterative process until a relaxed state of the system has been found. The analysis of the results is performed afterwards.

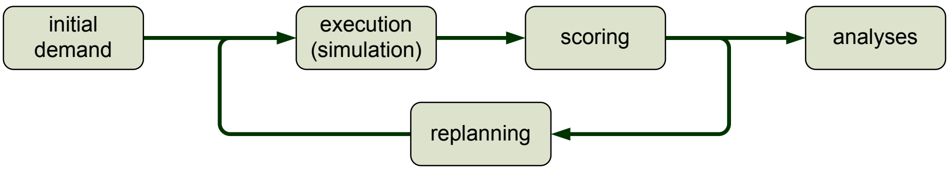

Figure 4: Iterative MATSim Loop

The loop contains the elements *execution (simulation)*, *scoring* and *replanning*. Within the simulation module, the plans of the agents are executed. Afterwards, the scoring module uses a utility function to calculate the quality of the executed plans. The utility function for MATSim is described by [19]. Finally, in the replanning module the agents have to select the plans which will be executed in the next iteration. Each agent can keep several plans in its memory. Bad plans can be deleted, new plans can be created by cloning and adapting (replanning) existing ones using information (e.g. travel times) from one or multiple previous iterations. The allowed replanning operations define the search space of the optimization (e.g. routes, location and start / end times of activities). Replanning modules currently under development will additionally allow to change order of the planned activities [21] as well as the locations where they are performed [20]. Multiple simulation modules are available [14, 22, 23] which offer additional functionalities like traffic signals [24], public transport [25] or the ability to adapt the agents' plans while the simulation is executed [26].

4 Exceptional Events in a Transport Simulation: Problem Definition

4.1 Iterative Simulation Approaches

Typically, agent-based traffic flow micro-simulations like MATSim use an iterative approach to optimize the traffic demand in a simulated scenario towards a user equilibrium. This iterative optimization can be seen as a period-to-period replanning strategy, meaning that the same period is simulated many times in an iterative process. After the period has been simulated, the results are evaluated and the agents' plans are replanned for the next iteration. However, due to the fact that one day is a very commonly used period duration, it is often denoted as day-to-day replanning strategy.

An iterative day-to-day replanning approach is appropriate as long as the scenario describes a typical situation or day. For such scenarios, it is feasible to assume, that the agents are familiar with the typically occurring events like traffic jams in the peak hours. Therefore, they can try to avoid driving during those times or use alternative routes with less traffic. However, if the scenario contains unexpected events that the agents cannot foresee (e.g. accidents or heavy weather conditions), using an iterative approach might not be the best choice. A first argument is, that a user equilibrium will not be reached in such a scenario because the agents do not have enough information to choose optimal routes and daily activity plans. Another problem is the optimization process itself. Even if an agent chooses its routes absolutely randomly due to a lack of information, it will find a good route if it searches long enough.

The Figures 5 to 8 show a simple example for a scenario, where an iterative approach would produce illogical and wrong results. In Figure 5, an agent's planned route in a sample network is shown. Additionally, the times when the driver passes each node of the route are contained. However, those times are only valid, if no exceptional event occurs. Figure 6 shows a link where an event like an accident happens which blocks that link for two hours. As a result, the agent reaches its destination two hours later than expected (Figure 7). When this scenario is iterated, the agent recognizes that this route has a much higher travel time than expected and therefore it will choose another route. The traffic jam caused by the accident will probably also increase the travel times on links next to the blocked link. Therefore, the agent might find a route which is quite different than the original one (Figure 8). However, a closer look at the node where the new route differs for the first time from the original route shows, that this happens even before the accident had happened, meaning that the agent "foresees" the accident.

An obvious solution to avoid problems like the ones described above, is using an alternative simulation approach without iterative optimization. The next section discusses such an approach and the requirements that it has to fulfill.

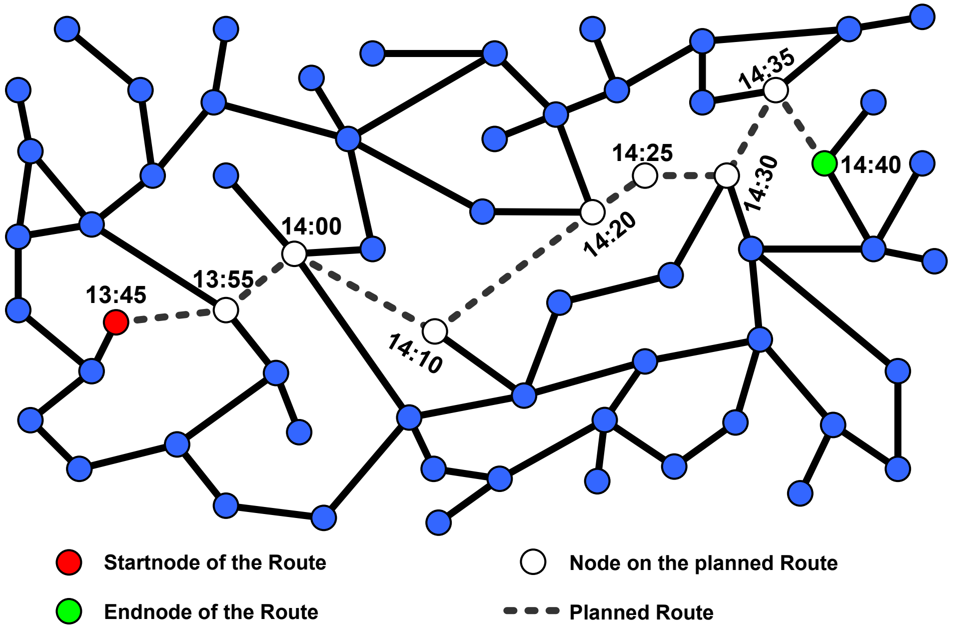

Figure 5: Network with planned Route

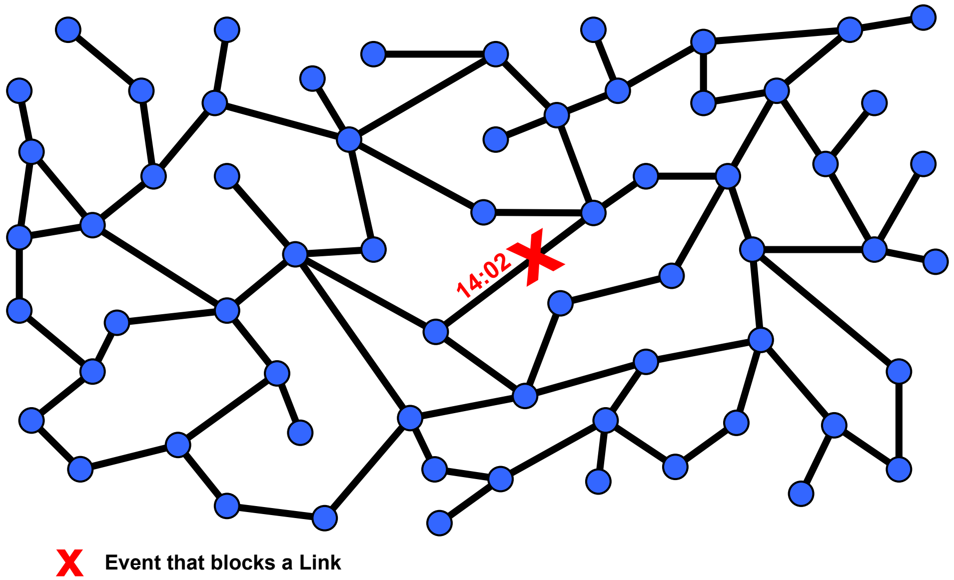

Figure 6: Network with exceptional Event

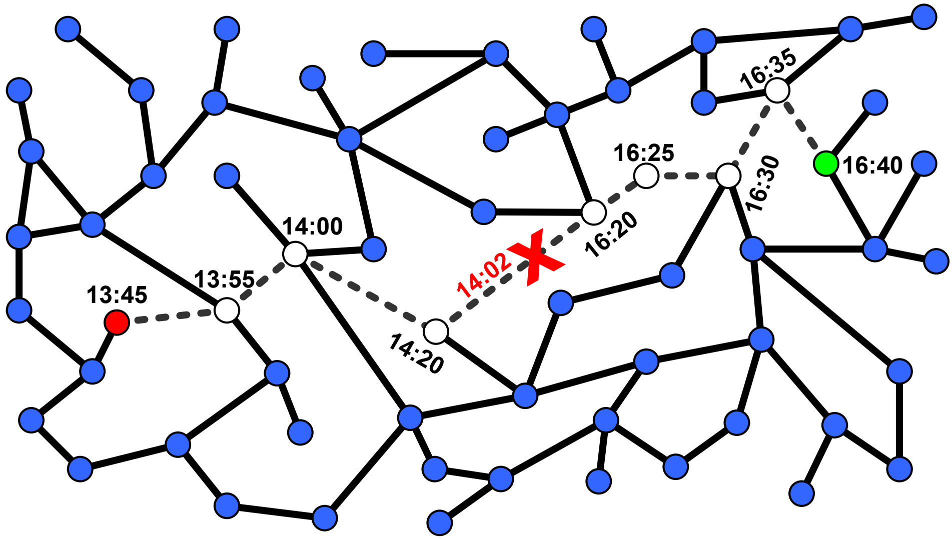

Figure 7: Network with exceptional Event and planned Route

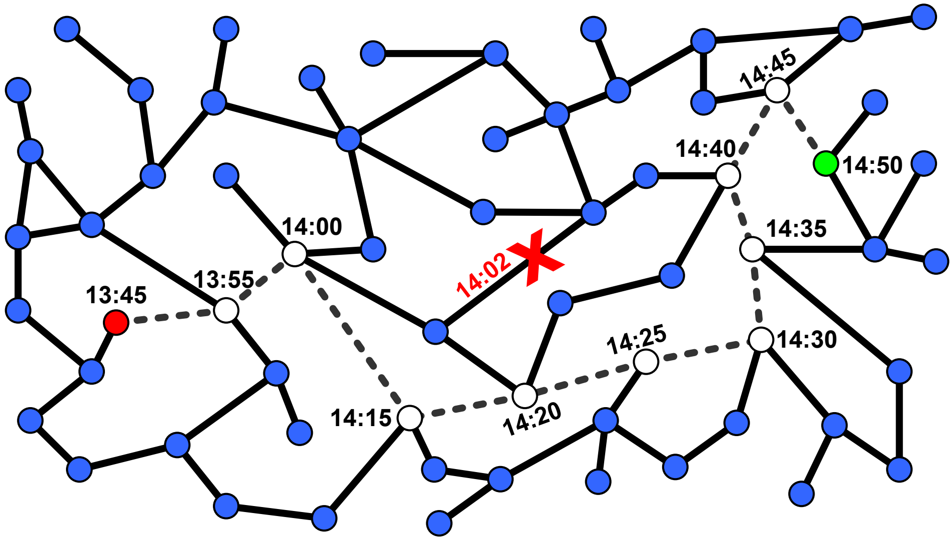

Figure 8: Network with exceptional Event and adapted Route

4.2 Within-Day Replanning Approach

A within-day replanning approach uses a strategy that differs significantly from one used by an iterative approach. Instead of multiple iterations only a single one is simulated. Thus, it is necessary that the agents can adapt their plans during this iteration without having information from previous iterations available. To to so, they have to continuously collect information and have to take into account their desires, beliefs and expectations when they decide how to (re)act.

While iterative approaches can use best-response modules, a within-day approach has to use something one might call a best-guess module. The travel times are an obvious example. In an iterative approach, the travel times can be collected over the previous iteration or even be averaged over several past iterations. The nearer a system is to a relaxed state, the smaller are the differences in the travel times between two iterations. This is not possible in a within-day approach. Even if an agent has perfect knowledge, it can only assume how the traffic flows will evolve in the future. To do so, it can take different sources of information into account to estimate the travel times. It could for example take travel times from a typical day without exceptional events and combine them with information it gathers during the simulated day. Depending on the amount and the quality of this information, the agent might rely more or less on its experience.

Therefore, information acquiring and the decision making process of an agent become important in a within-day replanning approach. In an iterative approach, each agent has total information and can therefore select the best route. Due to the limitation of available information, this is not possible in a within-day approach. One agent could for example choose a route where the expected travel time is very short but also very uncertain. Another agent might not be willing to take that risk and therefore select a longer route where the travel time is more reliable. Also the perception of information might vary between agents. One will probably rely on traffic information from the media, another one might ignore them.

Closely related to the expected travel times is the number, location and duration of performed activities. If an agent realizes that the travel times are higher than initially expected, it might react in various different ways. The agent could for example add or remove activities from its schedule, change their duration and order or perform them at locations that can be reached in shorter time. However, taking all these options into account results in a huge search space.

Due to the limited information available, a within-day replanning approach will, in contrast to an iterative approach, not converge to a user equilibrium. Decisions made during the simulated time period may seem to be optimal when they are made. However, if they are evaluated retrospectively, an agent might realize that they were not.

The objective in some typical applications for a within-day replanning approach is to minimize the difference between the user equilibrium and the results created using within-day replanning. An example is an *Advanced Traveler Information System* (ATIS). If the system provides reliable travel times, the agents will be able to find better routes and therefore the results will be closer to a user equilibrium. Another use case is the optimization of evacuation strategies. E.g. the application of supporting activities like providing route information to the evacuated people or creating contraflow lanes can be modeled and evaluated.

4.3 Combined Approaches

Besides iterative or within-day replanning only approaches, it is also possible to combine them. An obvious application is solving situations that cannot be planned exactly in advance like parking or car-sharing. An agent is for example able to plan a parking activity, but it cannot be foreseen which parking lots are available when the agents arrives. Thus, within-day replanning will be used when the agent starts to search a free parking lot. Other agents might want to share their car. To do so, it has to be ensured, that they really meet. This can be guaranteed using within-day replanning. If the driver arrives to early, a *waiting* activity is added to its plan, otherwise the picked up agent will perform a *waiting* activity until the car arrives.

5 Conclusions

Besides a short introduction into the topic of transport planning, the problems that occur with scenarios with exceptional events have been highlighted. A technique to overcome those problems has been presented.

There are many studies in the field of evacuations available. However, most of them are based on traditional techniques and suffer from the identified problems. Thus, additional research in the field of within-day replanning is required. On the one hand, the behavior model for the agents has to be improved. On the other hand, a model of the information distribution has to be developed.

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