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**Abstract.** This paper reports experiences with iterated traffic microsimulations in the context of a Dallas study. "Iterated microsimulations" here means that the information generated by a microsimulation is fed back into the route planner so that the simulated individuals can adjust their routes to circumvent congestion. This paper gives an overview over what has been done in the Dallas context to better understand the relaxation process, and how to judge the robustness of the results.

## 1 Introduction

The advent of ever more powerful workstation computers makes large scale transportation microsimulation projects feasible. At the same time, traditional tools are having a hard time treating all the complexities of modern congested transportation systems. As a result, there has been considerable progress in the area of transportation microsimulation in recent years, both in terms of theoretical understanding of micro-models [1–4] and in terms of practical implementations [5–11]. Yet, having good transportation microsimulations is only part of the problem. When running such a microsimulation, one finds oneself confronted with the question of how to "drive" it: when a driver in the microsimulation approaches an intersection, how does she know which way to proceed?

The traditional answer to this question are turning percentages: for example 50% of the vehicles go straight, 20% left, and 30% right. One is, though, immediately faced with a data collection problem: It is improbable that one knows the turn counts for all intersections of a regional area; and if one does not, one needs methods to "generate" the missing information [10]. Also, for transportation *planning* purposes one recognizes quickly that these numbers are not very useful because they change easily with infrastructure changes.

A somewhat better way is to use origin-destination matrices. Yet, the problems are the same: The information is not available, especially for non-work trips; and these matrices change with major infrastructure changes.

An answer to this is to start from demographics: It is improbable that people's income changes or that they move in a matter of weeks in response to transportation infrastructure changes. From there, for a *micro*simulation project, the first step is to generate "synthetic" populations from the demographic data [12]. The next task is to derive activities (sleep, work, shop, ...) for each member of a synthetic population, and then to derive the transportation demand from this. So far no project has succeeded in completely executing this program, i.e. to use activities based on demographics to "drive" a transportation microsimulation.

There are considerable challenges "on the way". For example, even when given a time-dependent origin-destination matrix and a traffic network, how does one allocate the trips to the network? Traditional assignment methods can be shown to be dynamically inconsistent under heavily congested conditions. One of the major problems is that for links where demand is higher than capacity, the link travel time depends on for how long the congested condition has been in place and not just on demand only, and thus the traditional link travel time functions are invalid.

A way out is to replace the traditional cost functions by a microsimulations. In short, one allocates traffic streams to the road network, runs the microsimulation and collects link travel times, re-allocates some of the traffic streams, re-runs the microsimulation, etc. This mimics "day-to-day" dynamics, i.e. "over night" some drivers decide to try a new route the next day. Obviously, one faces considerable challenges, such as: Which fraction of the population should be re-planned? How do we reach fast convergence of the process? Does the process converge at all? Can we measure convergence? Is a real traffic system converged? This paper will report results related to these questions in the context of a Dallas study. After providing the context (Sec. 2) and showing the first results (Sec. 3), the paper will summarize systematic feedback studies (Sec. 4) and possible "structural" convergence criterions (Sec. 5). After that, this paper will look at different aspects of the "robustness" of results; first under the change of a random seed (Sec. 6), then under the change of the complete microsimulation (Sec. 7), then in comparison to reality (Sec. 8). Section 9 discusses the robustness question in somewhat more general, pointing out that one first needs to define the question that the simulation is supposed to answer. The paper is concluded by a short summary (Sec. 10).

## 2 The context

The context of the results reported here is the Dallas/Fort Worth case study of the TRANSIMS project. The goal of the case study was to demonstrate that the approach has the general capability of generating output that is useful for stake-holder analysis and scenario evaluation [13]. The setting of the study was a 5 miles times 5 miles area ("study area") around the busy freeway intersection between the LBJ freeway and the Dallas North Tollway north of Dallas downtown. The problem was approached by starting out with a "focused network" and a production-attraction (PA) matrix. The focused road network contained *all* streets inside the study area, but got considerably thinner with increasing distance from the study area. A production-attraction matrix is essentially a 24-hour origin-destination matrix with some land-use information included (trips from work to home are entered as trips from home to work, with the result that the zones where trips originate in these matrices need to be residential zones).

The PA matrix for Dallas/Fort Worth contained approximately 10 million trips during a 24-h period.

Since TRANSIMS is a microscopic approach, the first thing that was done was to decompose the PA matrix into individual trips. This was done using a 24-hour time use function, i.e. each trip had a starting time, and the distribution of starting times reflected rush period traffic. Out of these trips, only the trips starting between 5am and 10am were considered. These trips were routed along the road network, and only the trips which went through the study area were retained (about 300 000 trips). This set of trips, sometimes called "initial planset", forms the basis of all studies presented here. See [13, 14] for further details.

## 3 First results

Just using the routes from the initial planset and sending them through a traffic simulation[1] typically generates a result as in Fig. 1, where many streets are occupied by jammed traffic. The problem behind this is, obviously, that the route generation phase for the initial planset did not take into account what other people were going to do. Yet, predicting what everybody else will do in a straightforward way is impossible; imagine yourself in a situation where you wake up one morning in a city where you need to go to work, and the only two pieces of information you have is a map of the transportation system and the information that everybody else is in the same situation as you.

The way we solve this is by iterations between microsimulation and planner. A possible method is the following: the microsimulation is run, link travel times are extracted from the microsimulation, a certain percentage of the travelers computes new routes based on these link travel times, the microsimulation is run again with these new plans, etc. New routes are computed using time-dependent fastest path based on the starting time, starting location, destination, and link travel times from the microsimulation. Other iteration schemes are possible, see, e.g., [15].

An open question here is which percentage of the travelers should be replanned. First, we started out with a fairly high percentage, 10%, and used that until the results started oscillating, which was after the 7th iteration.[2] In iterations number 8–12, 5% of the trips were re-routed; in iterations number 13–14, 2% of the trips. A typical result after 14 iterations can be seen in Figs. 2 and 3. Clearly, the traffic jams have cleared, and traffic is not only more evenly distributed, but because the system is more efficient, traffic does not back up.

[1] Note that this remark implies that we are using microsimulations based on *route plans*, i.e. each driver knows before her trip starts exactly the sequence of links she wishes to take through the network.

[2] The reason for the oscillation is easy to understand: Assume you have two route alternatives, and one is slightly faster. If you re-route a certain percentage of people, than the other alternative will be faster. Without additional measures, this will be an undamped oscillation.

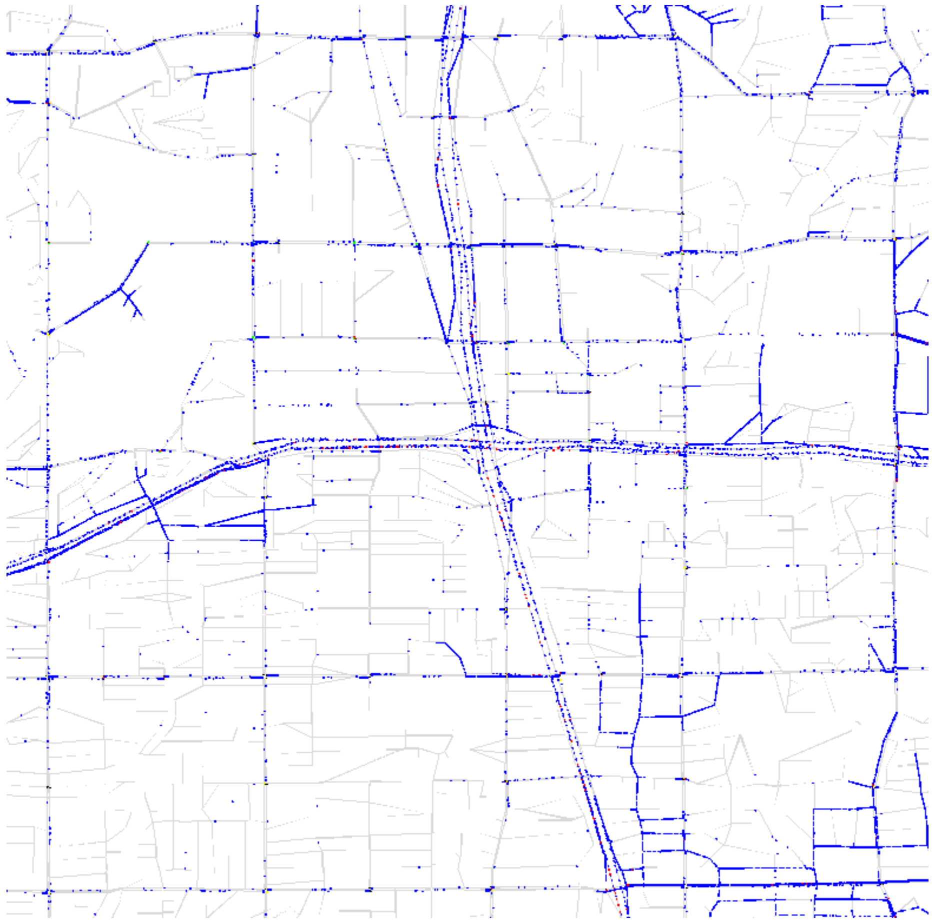

**Fig. 1.** Microsimulation run based on initial planset, snapshot at 9:30 am.

Fig. 2 looks "plausible", whereas Fig. 1 does not. Further information can be found in [14].

## 4 Systematic feedback studies

Using a relaxation scheme such as the above is not very practical (because it needs human supervision) and scientifically not very convincing: Questions such as "Does the process converge? If so, can we quantify 'distance' from the converged state? Is real traffic converged?" come up. One next step is thus to more systematically test relaxation schemes and relaxation properties. (Since we do not know if the process "converges" in the mathematical sense, we will talk about "relaxation" instead.) Rickert [5, 16] has run such tests in the same Dallas/Fort Worth context, but with a different microsimulation [6]. His microsimulation is

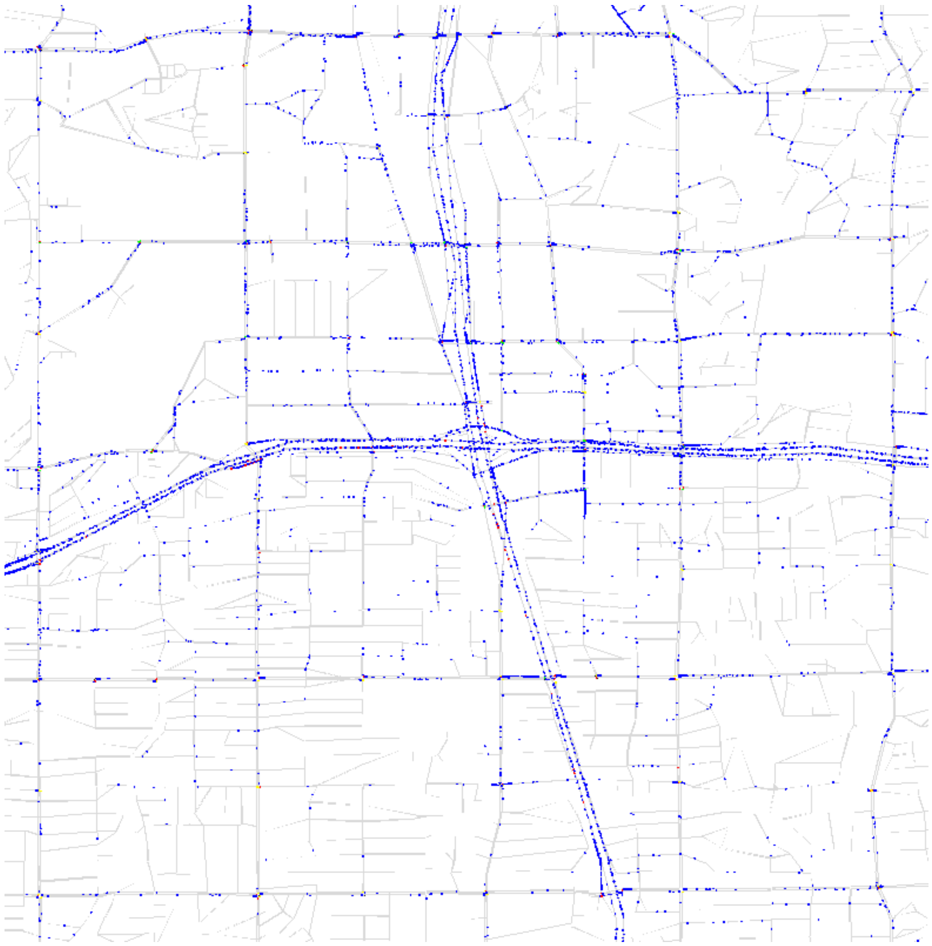

**Fig. 2.** Microsimulation run based on the planset after 14 iterations, snapshot at 9:30 am. Compare to Fig. 1.

somewhat less realistic (most important points: no signal plans, no turn pockets, no lane changing for turning behavior), but it currently runs more than 20 times faster than the microsimulation used in the last section. Some comparisons between the results obtained by both microsimulations will be shown below; we believe using a different microsimulation will not have any significant impact on the general results that will be discussed in this section.

Fig. 4 shows the sum of all travel times as a function of the iteration number for different iteration schemes. For example, the full line (also marked by +) is for the same relaxation scheme as described in the last section. The data marked by the $\times$ symbol is for an iteration series where in each iteration only 1% of the travelers was re-planned. The dotted lines are for iteration series where 5% of the

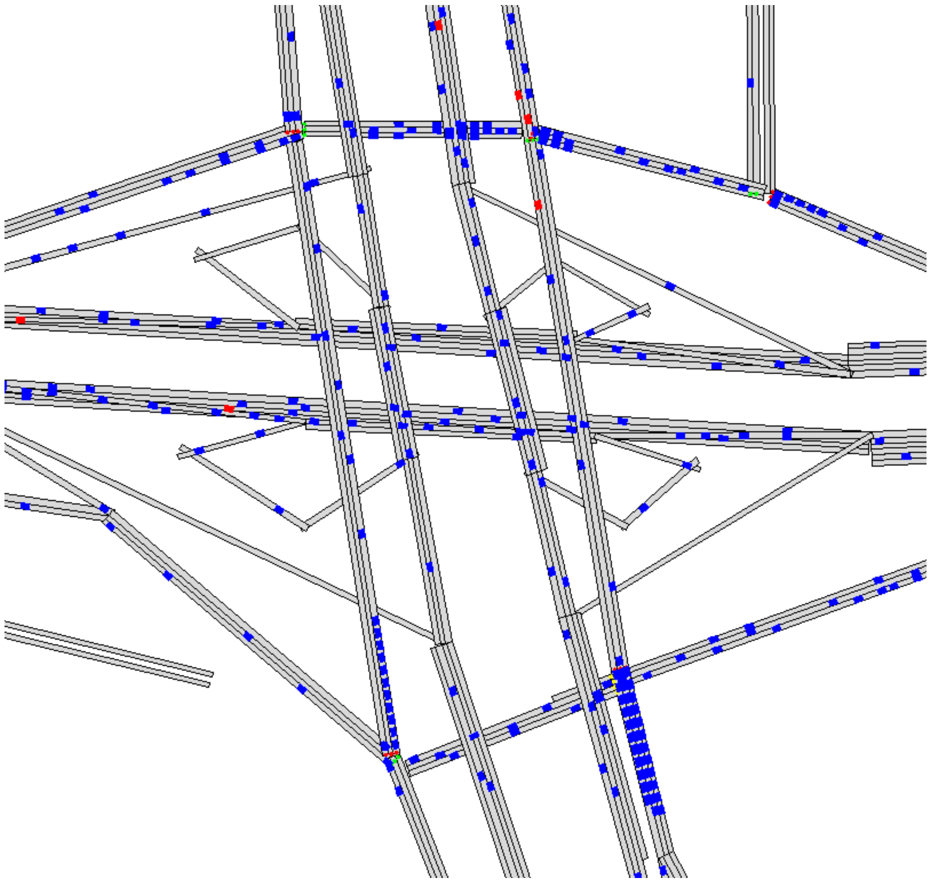

**Fig. 3.** Microsimulation run based on the planset after 14 iterations, snapshot at 9:30 am, detail. Traffic lights are shown by their colors at the end of links. Cars can be color coded according to specified criteria – in this specific example, cars that were not able to follow their intended plans because they could not get into the desired lane are shown red.

travelers were re-planned; in one case these 5% were selected randomly, in the other case they were selected according to "age": A traveler who had not tried a new route for a long time was more prone to re-planning. Several observations can be made from this plot:

– The simulations relax to a value of approx. $1.1 \cdot 10^8$ seconds for the sum of all travel times. Clearly, the iteration described by the full line and "+" is not yet there.
– The iterations marked by the $\times$ symbol are relaxing very slowly. The reason for this is that 1% re-planning means that the probability of *not* having been re-planned after 110 iterations is $0.99^{110} \approx 0.33$, i.e. about one third of all

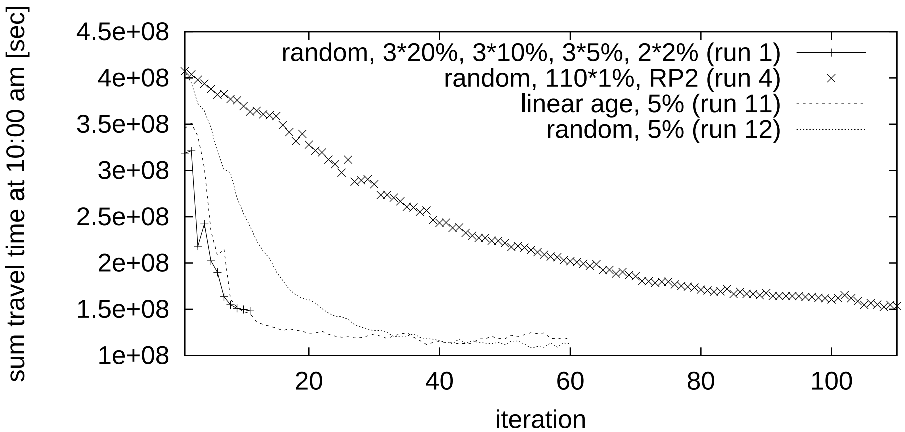


**Fig. 4.** Sum of all travel times as a function of the iteration. Clearly, the sum of all travel times decreases with the iterations because congestion clears and the efficiency of the whole system increases. Different iteration schemes result in different relaxation speeds. From [16].

trips still follow their initial route which has been computed without *any* feedback information.
- As the line for "age-dependent" re-planning shows, much faster relaxation schemes are possible even when they are non supervised.

For further information, see [5, 16].

## 5 Characteristics of fastest paths in relaxed vs. unrelaxed traffic situations

The above quantity, sum of all travel times, has the disadvantage that as a relaxation criterion it is only meaningful in the context of a relaxation series: One can follow its behavior, and from that one can decide that the series is now "relaxed" or not. This approach is not useful for answering the question where the "real" system is. Is it somewhere along such a relaxation line, but not quite at the bottom? Is it totally different? The sum of all trip times is a number that cannot be compared across different networks: That number would, for example, depend on the size of the region.

For answering such a question, one needs a more "structural" approach, one that looks "directly" at the properties that supposedly relax. The property that relaxes in the above approach is the "incentive to deviate". Our behavioral assumption is that people, given the starting time and location and the destination, will switch routes until they find a reasonably fast route. To a certain extent, this follows the traditional assumption both for the Wardropian equilibrium in transportation and for a Nash equilibrium in game theory in that rational players choose their best strategy (= fastest route), based on the assumption that everybody else is rational. Yet, in reality people do not search for the fastest route at all costs; also, the above relaxation scheme when inspected closer reveals that in it people do not select the route with the fastest *expected* travel time, even not in the average.

So the question becomes if we can measure a quantity which reflects the incentive to deviate; and if so, if this quantity decreased with the iteration numbers. A different way to formulate the question is: How much additional time would you need for your second-best route? One of the problems here is that "second-best" route is not well-defined; simply computing $k$–shortest paths in an algorithmic way will generate many solutions that most people will not consider alternatives; such as leaving a freeway at an off-ramp, crossing the intersection, and getting on again at the other side of the intersection. Yet, other approaches based on "reasonableness" cannot be considered satisfying for the present question [17].

In order to have a quantitatively sound criterion, we used $k$–fastest paths but then calculated the "difference to the fastest path". By this, one can distinguish between routes which differ only little from the fastest path and routes which differ a lot. We then plot that quantity as a function of, say, additional travel time. The information provided thus is (Fig. 5a): Given I accept $x$ seconds more travel time, how different are my possible routes from my fastest route? One can now calculate this information for many different origin-destination pairs. Averaging the resulting information for given amounts of additional travel time results in Fig. 5b, i.e. the figure provides an answer to the question: How different will my route be *in the average* from the fastest route if I accept $x$ seconds of additional travel time?

Now, note that the two curves in Fig. 5b have been computed with two different link travel time sets: (i) "unrelaxed congested" uses link travel times obtained from an "unrelaxed" simulation (i.e. based on the "initial planset") at a congested time of the day; (ii) "relaxed congested" uses link travel times obtained from a "relaxed" simulation (i.e. after many iterations) at the same congested time of the day. Clearly, when accepting a certain amount of additional travel time, the options one has under relaxed conditions are in the average much more diverse than under unrelaxed conditions. In other words, many different routes will provide near-optimum performance for the individual driver; the optimum becomes "flat". This means that the system arranges itself in a way that the "incentive to deviate" is fairly small, because even if you do not use the optimal route, the gains from switching are fairly small. For further information, see [18].

## 6 Random fluctuations

Our microsimulations are stochastic, i.e. they use random numbers during the computation of their dynamics. That means that a simple change of a random seed can change the entire dynamic trajectory of the simulation. Fig. 6 is

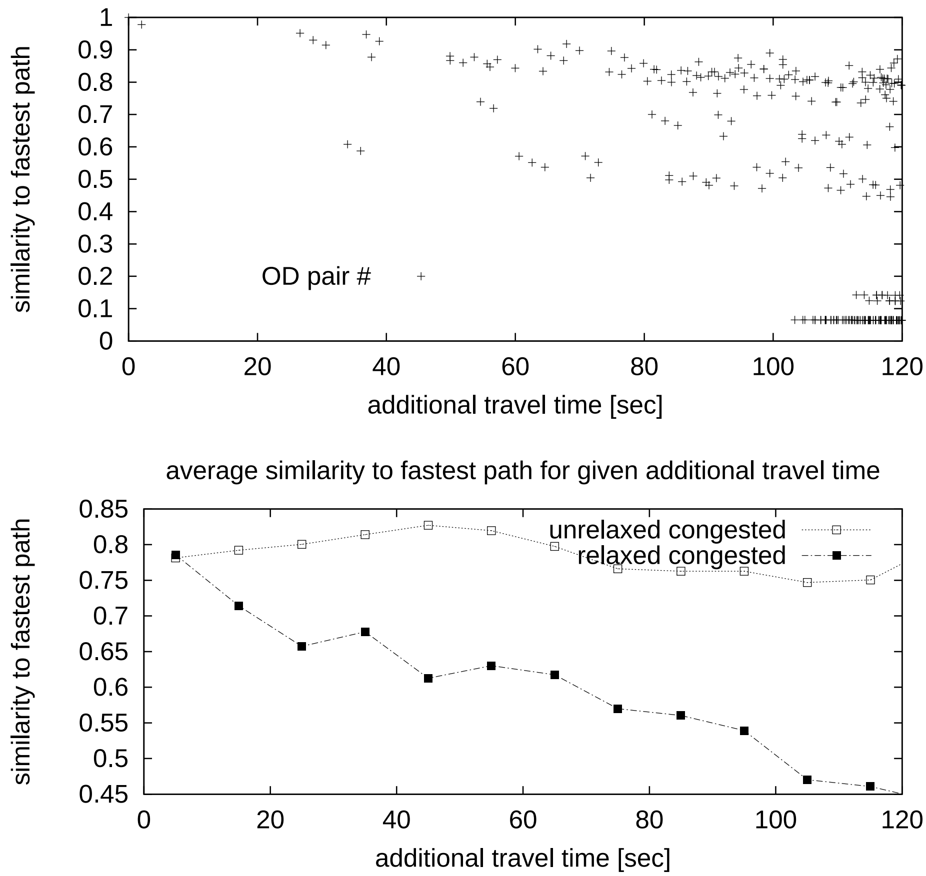


**Fig. 5.** Plotting "similarity to fastest path" as a function of "additional travel time". *Top:* Example. One observes that, if one allows more and more additional travel time, one obtains more and more options that are very different from the fastest option. *Bottom:* Average over 955 origin destination pairs. One sees that, for given additional travel time, one has more diverse options in the relaxed congested case. From [18].

an example how dramatically the situationcan change with only the change of a random seed shown (compare to Fig. 2). Clearly, using stochastic dynamics makes formal definitions, analytical proofs, and computational proofs of convergence much harder. Yet, we believe that it is a necessary feature of reality; also, it makes the computational search process more robust against getting "stuck" in implausible situations.

A result of stochasticity is that transportation simulation projects can, for any given question, at best return a "distribution" of possible answers, i.e. deterministic answers are not possible. Note that, if the distribution is not Gaussian,

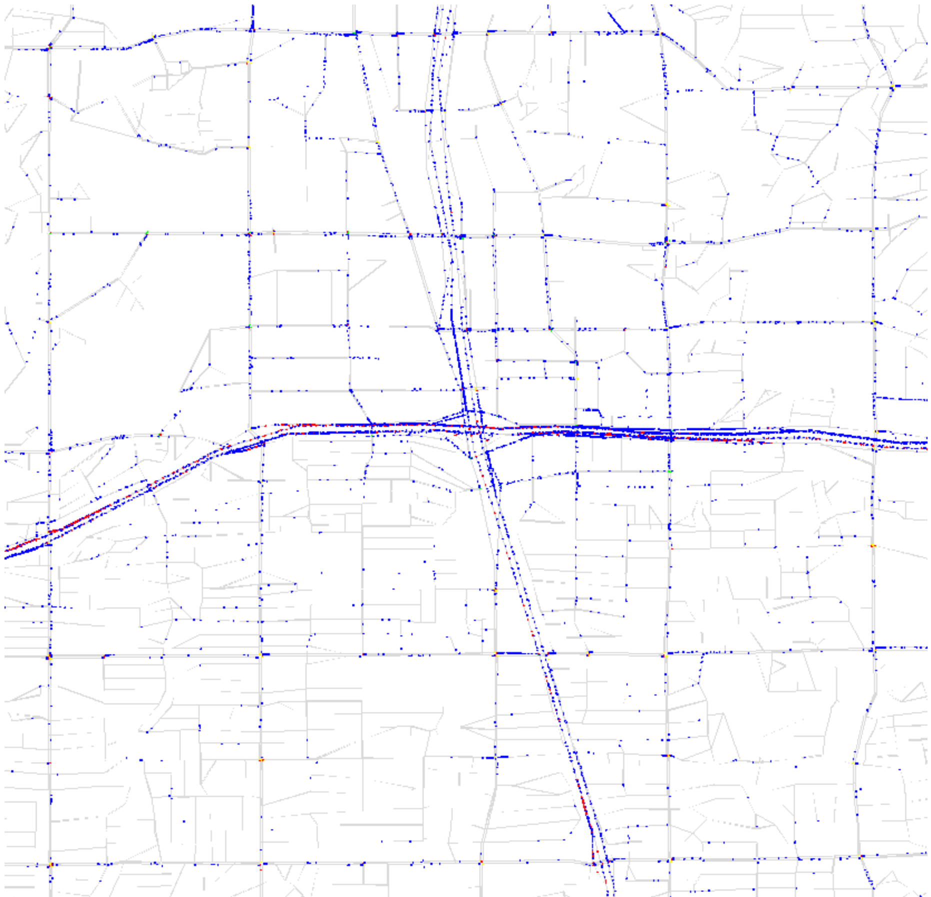

**Fig. 6.** Demonstration of random fluctuations. Microsimulation run based on planset after 14 iterations, snapshot at 9:30 am. Compare to Fig. 2, the only difference between the runs is a changed random seed.

then using the arithmetic mean as a replacement for the deterministic answer can be misleading, for example in the case of a bi-modal distribution.

This indicates that more systematic studies of the effects of stochastic dynamics need to be done.

## 7 Different microsimulations

At the current stage, it is unclear in how far transportation simulation projects will be able to provide "robust" answers to questions that are relevant to society. As a minimum requirement, one should be able to extract "similar" answers from different codes. Fig. 7 shows an example of using a different microsimulation in

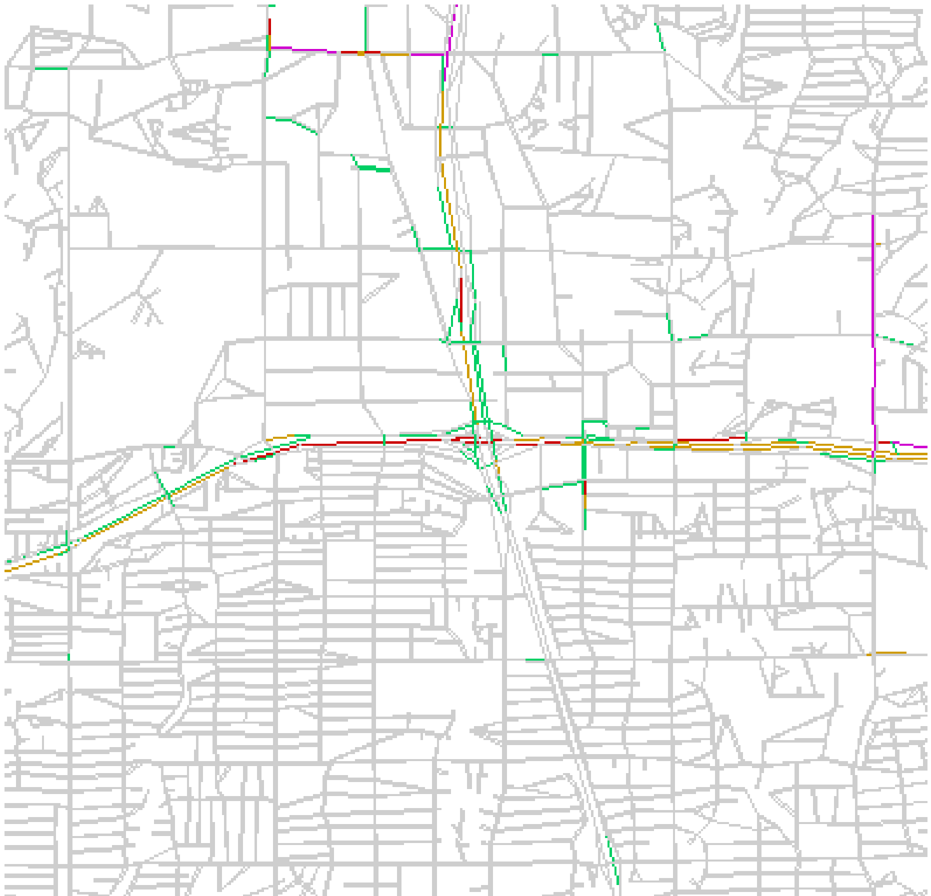

**Fig. 7.** Using a different microsimulation in the same study context. Compare to Figs. 2 and 6. Unfortunately, a plot showing individual vehicles as in the other plots was not available; but to a certian extent, a comparison is possible. Gray means link density (occupancy) below 10%, green means below 30% (which corresponds roughly to capacity), yellow means below 50%, red means below 70%, and purple means above 70%. From [16].

the same context; in fact, the microsimulation is the same as the one used for the results described in Sec. 4. The figure should be compared with Figs. 2 and 6. Clearly, there are similarities. Traffic on the eastern part of the east-west freeway is in general heavy whereas most of the other simulation area turns out to be outside the congested regime. In some sense, Fig. 7 is in between Figs. 2 and 6, which only differ by the initial random seed. Beyond these somewhat general observations, comparison between different microsimulations is not very well defined problem; see Sec. 9 for a further discussion of this subject and [19] for more information.

## 8 Comparison to reality

In the context of the Dallas study, we had some turn counts from selected intersections available. Before turning to the results, some details about the comparison have to be noted, which are a consequence of the fact that the north-south freeway in the study area did not exist in its full length before 1990:

- The main inputs for our microsimulations are the network and the trip tables (PA matrices).
- The trip table that we use is from before 1990, i.e. *before the northern part of the north-south freeway existed.*
- The network that we use is from after 1990, i.e. *after* the northern part of the north-south freeway was opened.
- The reality counts are from 1996, i.e. from a time where the network was similar to the one in the simulation, but the trips had adjusted to the existence of a much faster way to travel north-south in the northern part of the study area.

In consequence, we would expect that our studies underestimate north-south traffic in our study area compared to the 1996 counts.

When looking at Fig. 8, this is clearly the case. But this is not the only feature. One also notices that in fairly general our simulation over-estimates traffic on minor roads and through turns; this is most probably a consequence of the way the re-planner works because it *only* looks at travel times and not, for example, at inconveniences caused by sharp turns or by stop signs. These results reflect work in progress; further results will be published elsewhere [19].

## 9 Robustness of (micro-)simulation results

The previous two sections ask the question of how to compare different microsimulations or of how to compare microsimulations with reality. In principle, this should be easy: microsimulations generate microscopic observables, and so we simply extract the same information from the microsimulations and from reality and we compare them. Yet, it is unclear *which* information to exactly to extract: Which is the most meaningful information? For example, does the fact that microsimulation XYZ has 20% too many right turns on a certain intersection really matter? Or what is more important: 100 vehicles more at the end of an already large traffic jam, or 100 vehicles more on uncongested roads?

One needs to relate this problem to the question one attempts to answer with a specific simulation project. The level of fidelity of a simulation project will always depend on the level of effort spent; and it seems reasonable to us to adjust the level of effort to what is really necessary for a given question. Also, with a given question at hand, the problem of comparing simulations becomes better defined: One does not need any more to decide if two simulations are "equal", but only if two different simulations give the same answer to the specified questions. This latter approach is much better accessible to the statistical tools at hand;

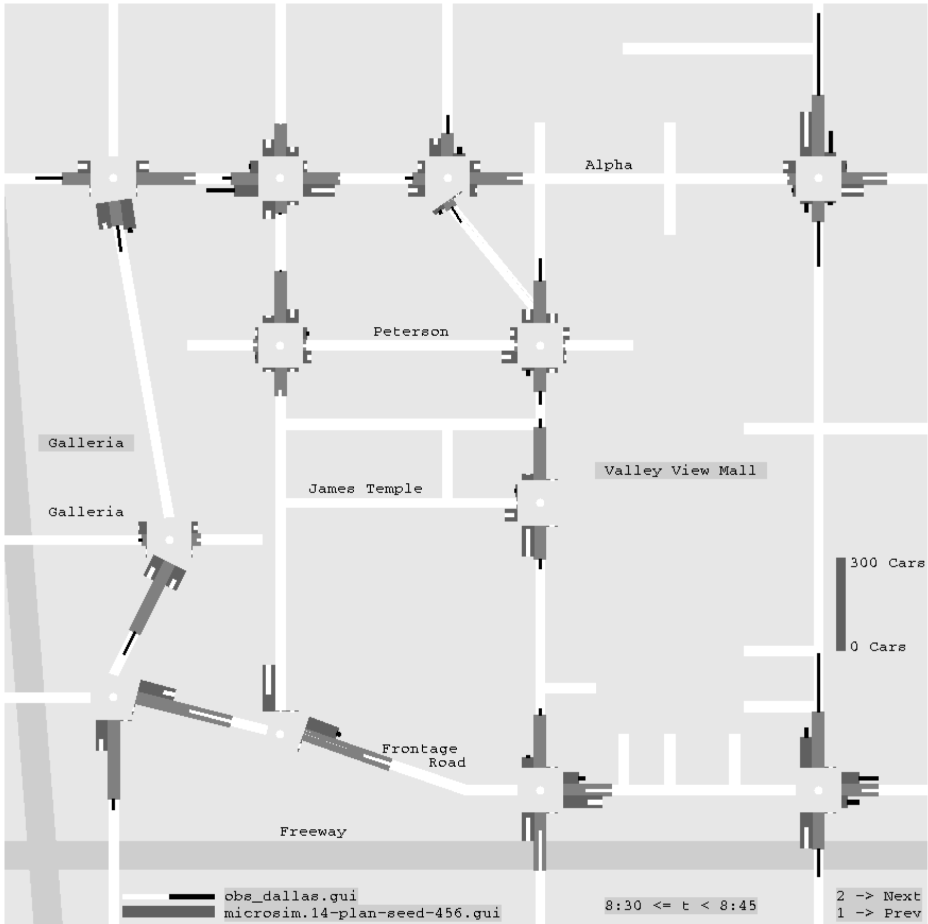


**Fig. 8.** Comparison with reality between 8:30am and 8:45am. At most intersections, there are three principal bars, one for right turns, one for traffic going straight, and one for left turns. For each of these principal bars, the middle (black/white) bar shows the observed value, the outside (gray) bar the value from the simulation. For example, for the intersection in the right upper corner, the simulation is underestimating both southbound and northbound through traffic. – When interpreting this figure, one needs to know that the rightmost north-south road and the topmost east-west roads are major arterials, the dark grey roads are freeways, roads immediately parallel to the freeways are frontage roads, and all other roads are minor. Only then it becomes clear that we are overestimating traffic that goes through “inconvenient” routes, i.e. through sharp turns and over minor roads. Also, we underestimate north-south traffic in general due to the data inconsistency described in the text. Note that we have made no attempt to “calibrate” the simulation to these values. From [19].

admittedly, it is not very satisfying because it means that for any new question one needs, in some sense, to start over.

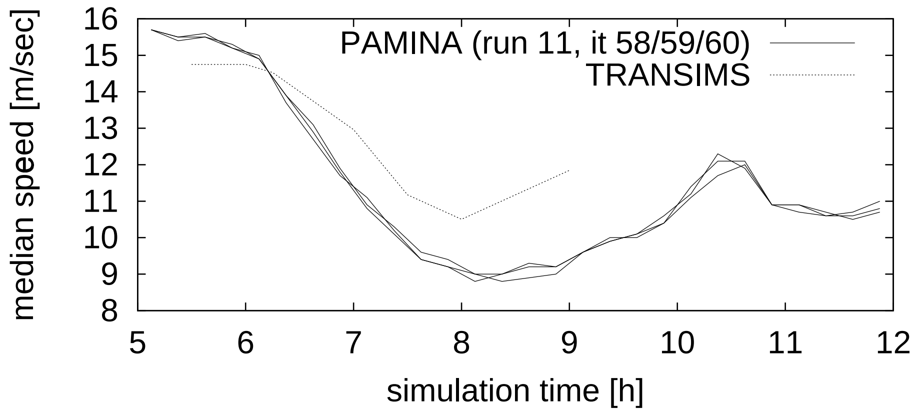


**Fig. 9.** Comparison of median "geographical" speeds between two simulations. What we mean by geographical speed is "geographical distance" divided by "travel time", i.e. *not* the average driving speed. This measures accessability of an area; in this case accessabiliby of the interior of the simulation area when coming from the outside. From [19].

Fig. 9 presents one such possible result. Plotted is the average speed for reaching the center of the simulation area when coming from the outside. The speed here is calculated by "geographical distance divided by trip time", i.e. it does *not* reflect driving speed but is a measure of "accessibility": Low speeds reflect that the destination is difficult to reach. Our plot is a simplified version of a type of questions that are really important in the context of "stake-holder analysis". For example, does the introduction of a light rail make travel to the downtown area faster for people who do not own a car? (Probably yes.) Does it make the same travel faster for people who own a car? (Probably not, at least not during uncongested conditions.)

Now note that Fig. 9 only gives part of the full answer. We certainly see that in both simulations, accessibility of the center of the simulated area drops during the morning rush period. We also see that the drop in accessibility is different between both microsimulations. Yet, if the question were for example to find the time of worst accessibility during the morning rush period, both simulations would give the same answer.

Last, but not least, note that this paper deliberately side-steps the question of the trustworthiness of the microsimulation itself. In this paper, we have concentrated on "macroscopic" aspects, such as large scale fluctuations and the interplay between route planner and microsimulation. Yet, it is also useful to test and document microscopic aspects of traffic models. The discussion of what to measure here and how is ongoing; but there seems to be some slowly growing consensus that certain building blocks of the flow characteristics, such as flow through a stop sign as function of the traffic on the major road, unrealistic as these examples may be, should be part of these systematic tests. The development of more complex test suites would certainly be desirable. For further information on this in the context of TRANSIMS, see [20].

## 10 Summary

Iterated transportation microsimulations provide a very powerful addition to the tools of transportation planning. Their power lies both in the capability to represent time-dependent scenarios in their "true" time-dependent dynamics and in the possibility to access individual, microscopic quantities directly. Yet, one needs to note that research in this area is at its beginning; no consistent theory is available to help and even the building of intuition is in its initial stages. This paper provides a summary of what has been done in the context of a TRANSIMS study of the Dallas area in order to provide exactly some of this intuition. These results can be summarized as follows: (i) Iterations between router and microsimulation adjust routes in a way that traffic becomes "plausible". (ii) The number of iterations that are necessary until the process is plausibly "relaxed" can be significantly reduced by using "intelligent" relaxation schemes. (iii) It seems possible to distinguish "unrelaxed" from "relaxed" conditions by looking at fastest paths in both situations. The result is interpretable in the sense that in relaxed transportation systems, there is not much difference in travel time between the strictly fastest path and very different routes. (iv) In stochastic microsimulations, simply changing the random seed can generate large fluctuations. (v) Using a different microsimulation in the same scenario produces results that look similar, but that are difficult to compare in general. (vi) Comparing to reality has the same caveats, plus the problem of data consistency. Nevertheless, the comparison provides useful insights. (vii) In general, comparison between microsimulations need to be geared to specific questions. An example of such a question is provided.

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