In: The Leading Edge of Travel Behavior Research, edited by D. Hensher and J. King, Pergamon, 2001, pp 659–681.

ITERATIVE DEMAND GENERATION FOR TRANSPORTATION SIMULATIONS

Jörg Esser[1] (a) and Kai Nagel[2] (b)

(a) Roland Berger Consulting, Germany

(b) Swiss Federal Institute of Technology Zürich (ETHZ)

ABSTRACT — New fast transportation micro-simulations make it possible to implement systematic computational feedback between travel demand generation (activities generation), route assignment, and a transportation simulation (network loading) while keeping a microscopic resolution throughout the whole process. Microscopic means that each agent (traveller) is represented microscopically. This report describes an implementation of such a computational feedback of micro-simulation results into the activities generation. The assignment of workplaces to home locations is used as an example. The workplace assignment is done in a way that the computation self-consistently finds a solution which reflects the trip time distribution from the census for home-to-work trips. Since the results of this can be expected to be reminiscent of the morning traffic, our resulting hourly volumes are compared with field data in Portland/Oregon and also with results of an earlier modelling study done by the Portland Transportation Planning Organization which uses more traditional methods. We find our results encouraging, especially when taking into account the relative simplicity of our assumptions.

keywords: traffic simulation; transportation planning; travel demand generation; activities generation

[1]Email: joerg_esser@de.rolandberger.com
[2]Corresponding author. Email: nagel@inf.ethz.ch. Postal: ETH-Zentrum IFW B27.1, CH-8092 Zuerich, Switzerland

1 INTRODUCTION

Several groups are developing simulations which can microscopically simulate whole metropolitan areas in faster than real time (e.g. DYNAMIT, 2000; MITSIM, 2000; Mahmassani et al, 1995 (DYNASMART); Rickert, 1998 (PAMINA); Gawron, 1998 (LEGO); Rakha and Van Aerde, 1996 (INTEGRATION); Esser, 1998 (OLSIM)). By "microscopic" we mean that each traveller is individually resolved. Thus, if one can generate detailed travel plans for each individual, these simulations can execute these plans, while recording for example where conflicts in the form of congestion delay the plans.

In consequence, it is only a question of time until it will be easy to couple such models with models of travel demand generation, as has been demanded for many years (e.g. Axhausen, 1990). Such a coupling will probably include a modal-choice-and-routing module ("router"), and it will do systematic feedback iterations between all the modules. That is, the results of the micro-simulation will be fed back into the router again and again until some relaxation with respect to route choice is obtained, and then the result will be fed back into the activities generation module, which will generate new activities which now take into account the slower speeds in the network caused by congestion.

In this paper, an early implementation of such a computational feedback of the microsimulation into the activities module is demonstrated. In fact, practitioners have often done some version of such a feedback, by adjusting origin-destination matrices in order to move the volume counts of the assignment model closer to reality. There are also computational procedures with respect to assignment models (e.g. Metaxatos et al, 1995). What will be done here is use such a computational procedure in connection with an explicit traffic microsimulation. We will however simplify in several ways: Cars will be used as the only mode, travel from home to work will be the only demand, and the traffic micro-simulation is rather simplified. The simulation will be iteratively adjusted towards the census trip time distribution. This is an early step, and we expect much progress in the near future. In particular, we expect that transportation microsimulation, where each traveller is individually resolved, will lend itself much better to integration with activity-based demand generation than the aggregating technique of traditional assignment does. Although the focus of our work was the compuration integration of dynamic traffic assignment with demand generation, we will compare our results with existing volume counts in the Portland/Oregon area.

The structure of the paper is as follows: In Sec. 2, the problem is stated, followed by a description of our approach with respect to demand generation and feedback (Sec. 3). After a discussion of related work (Sec. 4), the paper moves on to our actual study (Sec. 5) and its results (Sec. 6). The paper is concluded by a discussion and a summary.

2 PROBLEM STATEMENT

In general, we want to generate "realistic traffic" via computer simulation. Thus, our ultimate research goal is to have a model which, when applied to today's situation, will yield today's traffic, and when applied to a hypothetical scenario, will yield a meaningful prediction. In our actual implementations, however, we (as everybody else) make simplifications. We are, however, not interested in optimal solutions of the simplified problems; our interest is how close to reality we can get with our simplified models and computational procedures.

We envisage that such a realistic computer simulation will be a combination of population generation, activities generation, routes assignment, and traffic micro-simulation, coupled via feedback iterations. So what is done in the following is to pick (simple) versions of these modules, embed them into feedback iterations, and try this on real world input data. The research question was twofold: (1) What are the computational issues? (2) How close to reality (or not) does one get with simple assumptions?

The question of the necessary degree of realism in each of these modules is an open problem which will need further research. That question is not treated in this paper. We do not claim that the degree of realism (or not) chosen in any of the modules used for our investigation is the correct degree of realism in order to obtain meaningful results. In particular, we expect that more sophisticated demand generation techniques (e.g. Bowman, 1998; Doherty and Axhausen, 1998; Arentze et al, 1998) will lead to more realistic results. We do expect, however, that a systematic inclusion of transportation network impedance, as demonstrated in our study, will contribute to better and more robust models.

The problem for this paper is how to assign workplace locations to workers via using computer simulation. It is known from data where people live, and it is also known where they work, but one has to match these two sets of data. The problem is similar to the trip distribution step in the four step process. In the work described here, this is done via some strongly simplified assumptions. One of these simplifications is to only look at traffic resulting from people driving from home to work. By this one neglects, for example: delivery trucks, people returning from night shifts, travelers using alternative modes of transportation, etc. There is also much more complexity in the afternoon peak than in the morning peak. Again, our investigation is a demonstration of a computational procedure, not an attempt to obtain the most possible realistic results for a certain field problem.

Having said that, let us describe our scenario. Our scenario area is Portland in Oregon. Our input data are: (a) a description of the Portland transportation network; (b) a synthetic population based on Portland demographic data; (c) a list of workplaces including location and size; (d) the distribution $N_{cns}(T)$ of actually encountered trip times T from home to work by the Portland population; and (e) a distribution of starting times. The problem for this study was to match workers (who have home locations) and workplaces such that the resulting traffic yields trip times which, when aggregated, match the census trip times.[3]

[3]Since the whole travel of each traveller in our simulation consists of exactly one trip, "trip time" and "travel time" will be used synonymously.

3 OUR APPROACH

The approach that is maybe closest to our work are the discrete choice models (Ben-Akiva and Lerman, 1985). As is well known, in that approach the utility V_i of an alternative i is assumed to have a systematic component U_i and a random component η_i. Under certain assumptions for the random component this implies that the probability p_i (called choice function) to select alternative i is

$$p_i = \exp(\beta U_i) / \sum_k \exp(\beta U_k) \ . \tag{1}$$

p_i could for example represent the probability to accept a workplace that is i seconds away. If i is indeed taken as time, then U_i is negative, and it follows an inverse S-shaped curve which starts at zero, decreases slowly for small times, decreases faster for medium times, and decreases again slowly for large times (Bowman, 1998). By this approach, our above location choice problem would be solved by weighting each given workplace according to time-distance i by p_i and then making a random draw in these probabilities. Clearly, for the discrete choice approach one needs to know the function βU_i.

In this paper, the "psychological" function βU_i is obtained from "observed" trip time distributions, using new methods of micro-simulating large geographical regions. The core idea is that an observed trip time distribution $N_{tr}(t)$ can be decomposed into an accessibility part $N_{acs}(t)$ and an acceptance ($=$ choice) function $f_{ch}(t)$

$$N_{tr}(t) = N_{acs}(t)\, f_{ch}(t) \ . \tag{2}$$

$N_{acs}(t)$ is the number of workplaces at time-distance t; $f_{ch}(t)$ is proportional to the probability that a prospective worker will accept this trip time. Thus, apart from normalization f_{ch} is the same as the choice function in discrete choice theory. Our decomposition allows to separate the network specific accessibility distribution $N_{acs}(t)$ from the "psychological" trip time acceptance function. In principle, $f_{ch}(t)$ as found via our relaxation method should be the same as when obtained via an estimation of a survey when suitably averaged over the whole population.

Given a micro-simulation of traffic, $N_{acs}(t)$ can be derived from the simulation result. For a given home location (and a given assumed starting time), one can build a tree of time-dependent shortest paths, and every time one encounters a workplace at time-diestance t, one adds that to the count for trip time t. The challenge is that this result depends on the traffic: Given the same *geographic* distribution of workplaces, these are farther away in terms of trip time when the network is congested than when it is empty. That is, given the function $f_{ch}(t)$, one can obtain the function $N_{acs}(t)$ via micro-simulation, i.e. $N_{acs}(t) = G[f_{ch}(.)](t)$, where G is the micro-simulation which can be seen as a functional operating on the whole function $f_{ch}(.)$. The problem then is to find the macroscopic (i.e., averaged over all trips) function $f_{ch}(.)$ self-consistently such that, for all travel times t,

$$N_{tr}(t) = G[f_{ch}(.)](t)\, f_{ch}(t). \tag{3}$$

For this, a relaxation technique is used. It starts with a guess for $f_{ch}(t)$ and from there generates $N_{acs}(t) = G[f_{ch}](t)$ via simulation. A new guess for $f_{ch}(t)$ is then obtained via

$$f_{ch}^{(n+1)}(t) = N_{tr}(t) / N_{acs}^{(n)}(t) \ . \tag{4}$$

A fraction f_{act} of all travelers will do their workplace selection again, using the new $f_{ch}^{(\ + \ )}$. $G[.]$ is generated again via micro-simulation, and this is done over and over again until a sufficiently self-consistent solution for $f_{ch}(t)$ is found.

Real census data is used for $N_{tr}(t)$ (see "census-100"-curve in Fig. 3; from now on denoted as $N_{cns}(t)$). People usually give their trip times in minute-bins as the highest resolution. Since our simulation is driven by one-second time steps we need to smooth the data in order to get a continuous function instead of the minute-histogram. Many possibilities for smoothing exist; one of them is the beta-distribution approach in Wagner and Nagel (1999). Here, we encountered problems with that particular fit for small trip times: Since that fit grows out of zero very quickly, the division N_{tr}/N_{acs} had a tendency to result in unrealistically large values for very small trip times. We therefore used a piecewise linear fit with the following properties: (i) For trip time zero, it starts at zero. (ii) At trip times 2.5 min, 7.5 min, 12.5 min, etc. every five minutes, the area under the fitted function corresponds to the number of trips shorter than this time according to the census data.

Obtaining $G[f_{ch}]$ itself via simulation is by no means trivial. It is now possible to micro-simulate large metropolitan regions in faster than real time, where "micro"-simulation means that each traveler is represented individually. The model used here is a simple queuing type traffic flow model described in Simon and Nagel (1999). However, even if one knows the origins (home locations) and destinations (workplaces), one still needs to find the routes that each individual takes. This "route assignment" is typically done via another iterative relaxation, where, with location choice fixed, each individual attempts to find faster routes to work. Rickert (1998) and Nagel and Barrett (1997) give more detailed information about the route-relaxation procedure; see also Fig. 1 and its explanation later in the text.

Once $f_{ch}^{(n+1)}(t) = N_{cns}(t)/N_{acs}^{(n)}(t)$ is given, the workplace assignment procedure works as follows: The workers are assigned in random order. For each employee the time distances t for all possible household/workplace pairs *[hw]* are calculated, while the home location h is fixed and taken directly from the household data for each employee. Let t_{hw} be the resulting trip time for one particular *[hw]* and $n_{wo}(w)$ the number of working opportunities at workplace w. Then, an employee in household h is assigned to a working opportunity at place w with probability

$$p_{hw} \propto n_{wo}(w) f_{ch}(t_{hw}). \tag{5}$$

In addition to work location, home-to-work activity information also includes the times when employees start their trip to work. These are directly taken from the household data.

The complete approach works as follows:

(1) Synthetic population generation: First a synthetic population was generated based on demographic data (Beckman et al, 1996). The population data comprises microscopic information on each individual in the study area like home location, age, income, and family status.

(2) Compute the acceptance function $f_{ch}(T)$. This is done as follows:

(2.1) For each worker i, compute the fastest path tree from his/her home location. Compute the resulting workplace distribution $N_{wp}(i,T)$ as a function of trip time T.[4]

(2.2) Average over all these workplace distributions, i.e.

$$N_{wp}(T) := \langle N_{wp}(i,T)\rangle_i := (1/N)\, \sum_i N_{wp}(i,T)\ , \tag{6}$$

where N is the number of workers, which is by definition also equal to the number of workplaces. $N_{wp}(T)$ is thus equivalent to our earlier $N_{acs}(T)$.

(2.3) Compute the resulting average choice function via

$$f_{ch}(T) \propto N_{cns}(T)\,/\,N_{wp}(T)\ . \tag{7}$$

In addition, a normalization constant needs to be computed such that

$$\sum_T f_{ch}(T) = 1\ . \tag{8}$$

(3) Assign workplaces. For each worker i do:

(3.1) Compute the congestion-dependent fastest path tree for the worker's home location.

(3.2) As a result, one has for each workplace the expected trip time T. Counting all workplaces at trip time T results in the individual accessibility distribution $N_{acs}(i,T)$.

(3.3) Randomly draw a desired trip time T^* from the distribution $N_{acs}(i,T)\, f_{ch}(T)$.

(3.4) Randomly select one of the workplaces which corresponds to T^*. (There has to be at least one because of (3.1).)

(4) Route assignment: Once people are assigned to workplaces, the simulation is run several times (5 times for the simulation runs presented in the paper) while people are allowed to change their routes (fastest routes under the traffic conditions from the last iteration) as their workplaces remain unchanged.

(5) Then, people are reassigned to workplaces, based on the traffic conditions from the last route iteration. That is, go back to (2).

This sequence, workplace reassignment followed by several re-routing runs, is repeated until the macroscopic traffic patterns remain constant (within random fluctuations) in consecutive simulation runs. For this, one looks at the sum of all people's trip times in the simulation. The simulation is considered relaxed when this overall trip time has leveled out.

[4] In contrast to the routing module, no time-dependence was used here although future implementations should do so.

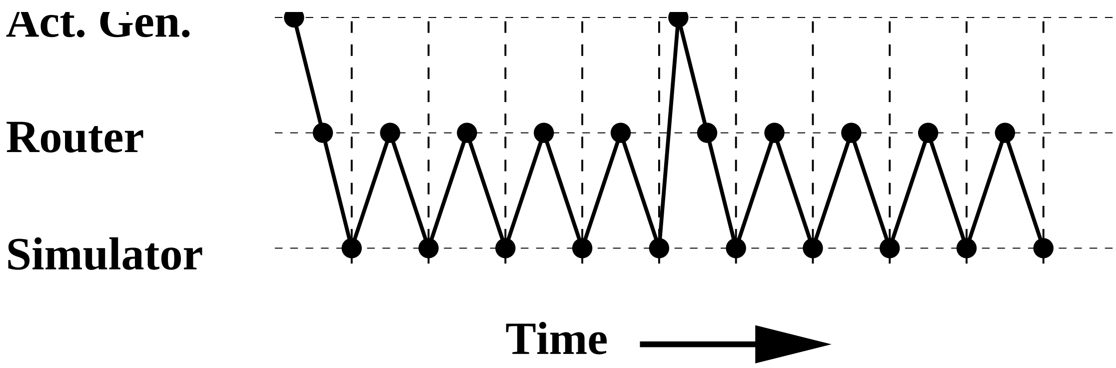

Figure 1: Iterative Activity Re-Assignment: Schematic subsequent application of activity generator, router, and traffic simulator.

Running this on a 250 MHz SUN UltraSparc architecture takes less than one hour computational time for one iteration including activity generation, route planning, and running the traffic simulator. The 70 iterations necessary for each series thus take about 4 days of continuous computing time on a single CPU.

4 RELATED WORK

The topic of this paper is a computational procedure of how to systematically feed back the results of a dynamic traffic assignment (DTA) to demand generation. In principle, any route assignment could be used instead of ours. However, since our work are steps towards a completely microscopic simulation approach, we are primarily interested in simulation-based route assignment and network loading. For this, one needs traffic flow simulations where one is able to follow each vehicle individually. Some simulations which fulfill this requirement besides the queue simulation used in the paper are: PAMINA (Rickert, 1998); the TRANSIMS main micro-simulation (TRANSIMS, 1992); LEGO (Gawron, 1996); INTEGRATION (Rakha and Van Aerde, 1996); DYNASMART (Mahmassani et al, 1995); PARAMICS (1996); MITSIM (Yang, 1997); DYNAMIT (2000); DYNEMO (Schwertfeger, 1987) or VISSIM (2000). Out of these, probably only LEGO, DYNASMART, DYNEMO, and DYNAMIT are fast enough to run iteration series such as ours on a single CPU. Within these four, LEGO is based on a queue model very similar to ours, while the other three use macroscopic equations for the movement of the vehicles.

In terms of re-routing during the route iterations, we use a standard time-dependent fastest path Dijkstra (see, e.g., Jacob et al, in press) based on 15-min link trip time averages. However, for this paper only a fraction of the population is re-planned. A widely used alternative is to re-plan 100% of the population in each iteration but to use a discrete choice approach approach to spread travelers across different routes (Cascetta and Papola, 1998; Bottom, 2000). Besides different theoretical properties, these approaches also have different computing complexities. The time complexity of our approach for the routing is $O(f\,N\,E \log\,K)$, where N is the number of travelers, f is the re-planning fraction (usually 10% in this paper), and $E \log\,K$ is the complexity of the Dijkstra algorithm where E is the number of edges and K the number of nodes. Note that this is independent of the time resolution. The approaches which re-plan everybody usually exploit the fact that, for any given starting location, one obtains the complete shortest path calculation for *all* destinations with the same worst case complexity as the calculation for just one destination. One thus obtains $O(F(\Delta T)\, M\, E \log\ K)$, where M is the number of possible starting points (traditionally zones) and $F(\Delta T)$ is some function that increases with increasing time resolution (decreasing ΔT) (Chabini, 1998). Since in our work each link is a potential starting point, this translates into $O(F(\Delta T)\, E^2 \log\ K)$. In this paper, where $E \approx 20k$, $N \approx 500\,000$, and $f = 0.1$, the two approaches are about equivalent. For street networks with higher resolution, E grows while N remains constant, making our approach grow more slowly in time complexity.

Also the workplace assignment is an old problem. An example of such a matching is the classic “Hitchcock” solution (Sheffi, 1985), where the workplace assignment is done in such a way that the overall sum of all trip times is minimized. This clearly results in much shorter trips than in reality. Axhausen (1990) suggests to couple demand generation, route assignment, and traffic simulation, although he puts more emphasis on on-trip learning than in the implementation presented here. Several groups such as the groups of Ben-Akiva or Mahmassani are actively working on this as extensions of their ITS projects. We are not aware of any results of these attempts yet. There are also earlier versions of the work presented in this paper (Wagner and Nagel, 1999, Esser and Nagel, 1999).

5 EXPERIMENTAL SETUP AND SIMULATION RESULTS

The study described in this paper was carried out as part of the TRANSIMS project (TRANSIMS, 1992), which was at that time aimed at simulating the whole city of Portland microscopically (i.e., with resolution down to single individuals) under consideration of activity generation, modal choice and route planning, and transportation dynamics. The simulations described in this paper were run on a road network consisting of 8,564 nodes and 20,024 links representing a subset of the real network.

Traffic counts for validation are available for 495 links comprising flow data for the morning peak from 7:15am to 8:15am. Data are available for the years 1992 and 1994. Data for 1992 is used for those links for which no 1994 data are available (68 links); for all other links, the counts of 1994 are used.

The data were collected using pneumatic road tubes and averaged over two or three weekdays; mostly on Tuesdays, Wednesdays, and Thursdays outside of holiday periods and while school was in session. The counts are not seasonally adjusted. Axle adjustment factors are applied to account for trucks, which are not explicitely counted. The accuracy of the counts is considered to be $80 - 85\%$ (Bill Stein, Portland Metro, personal communication).

Another set of data available are the results of assignment runs by Portland Metro. These runs use their own demand generation, and the EMME/2 assignment algorithm (Babin, 1982). Note that “EMME/2” results in this paper will refer to results of that particular study by Portland Metro including its demand generation.

One problem with our census based assignment approach is that trip times are overestimated for at least two reasons:

(1) First, when people are asked for the time they spend for their trip to work they usually report the total door to door time including the time to get to the car or park the car. On top of that, people tend to overestimate the time they spend driving especially in stop-and-go traffic (K. Lawton, personal communication).

(2) Second, the road network used for our simulation does not cover most minor streets. That means the time people spend on these roads should be taken out of the distribution.

The amounts of those times can however not be estimated without further information. To get an idea whether a trip time distribution which is shifted to lower trip times yields more realistic results, two different workplace assignment iterations were done: One with the original census distribution, and another with all desired travel times reduced to 80% of the original value. In the following we refer to these runs as run sim-100 and sim-80, respectively.

In Fig. 2 the total trip time is plotted for both series, sim-100 and sim-80. Each simulation run refers to running the queue simulation for the morning (from 4am till 12pm). After every 5 iterations in which people are rerouted only, people are assigned to new workplaces. This can be seen as a sudden, normally upward jump of the total trip time in the plot. The reason for the jump is that it takes some reroute iterations to adjust the routes to the changes in the trip demand pattern. We ran 20 route iterations after the last workplace assignment to make sure that the routes are actually relaxed.

As expected, the total trip times are lower for sim-80 (Fig. 2). Yet, it is striking that a decrease in desired trip times by 20% results in actual trip times which are about 50% lower. The reason will be explained in the next paragraph.

By looking at the trip time distributions in the simulation (Fig. 3), it can be seen that the resulting distribution for sim-80 is closer to the corresponding census distribution than it is for sim-100. Even after assignment and route relaxation, there are still a lot of unrealistically high trip times for sim-100. This results from the fact that the overall traffic demand is more than the network can carry, leading to a lot of congestion. It is well known that large fluctuations occur when transportation systems are operated with demands that exceed capacities (Kelly, 1997; Nagel and Rasmussen, 1994). Actually, detailed investigation shows that in each simulation run different people account for the very high trip times, which underlines the influence of large fluctuations. Also for sim-80, the distribution resulting from the simulation does not perfectly match the corresponding modified census distribution. Nevertheless, the effect of large fluctuations due to congestion is smaller than for sim-100. These erratic occurrences of large trip times are also the reason why the reduction of the desired trip times by 20% leads to a decrease in actual trip times by 50%: In sim-100, the system is simply not capable to find a solution that is able to match the demand, and thus has too few contributions at trip times around 500 secs while it has too many contributions at trip times above 3000 secs.

As mentioned above, we do not claim that the 80% census trip time distribution leads to a realistic representation of the real traffic flows in the study area. The idea is just to check the assumption that a reduced distribution leads to more realistic traffic flow patterns. The comparison with the field data is topic of the following section.

6 COMPARISON TO FIELD DATA AND TO EMME/2 STUDY RESULTS

First, the field count data is compared with the results of our simulation runs directly for every link. For comparison, the results of the "EMME/2 study" are also shown. Fig. 4 shows the typical scatterplots, with field data on the x-axis and simulation results for the same links on the y-axis. Note that both axes are logarithmic.

The first observation is that the plots look remarkably similar in structure. All three studies give relatively unbiased results for high flows, and underestimate low volumes. In addition, there are a few data points where simulation and reality are rather far apart.

At closer inspection, one notes that EMME/2 is somewhat overestimating high volumes, whereas our simulations are underestimating them. This is confirmed by bias calculations (see below). Such an effect is consistent with what one would expect: The Portland Metro assignment model for the presented results does not have a flow cutoff at capacity, so that it is possible to actually put more flow on a link than that link has capacity. This happens in particular at bottlenecks on short links in an otherwise relatively uncongested area.[5] The queue model traffic simulation tends to behave in the opposite way. If demand is higher than capacity, the queue spills back. Once this queue reaches another intersection, that intersection will normally be blocked for all directions, not just for the direction into the congested link. This is a consequence of the fact that the queue model neglects multi-lane effects at intersections. This means, for instance, that a car waiting for a chance to make a left turn blocks all following cars on this link. This tends to cause unrealistically large spill backs.

When one compares sim-80 to sim-100, the flows for sim-80 are closer to the field data for high volumes, and farther away for medium volumes. It is striking that demand reduction by as much as 20% changes the resulting flows so little. This adds to the conjecture that measured flows in a network depend as much on the network structure as on the demand structure.

For more detailed information, one can look at links in different classes regarding field data and direction (Table 1). For each class c we calculated the mean absolute and relative bias, i.e.

$$b_{abs,c} = (1/N_c) \sum_i (x_i - \xi_i) = (1/N_c) \left(\sum_i x_i - \sum_i \xi_i \right) \quad \text{and} \quad b_{rel,c} = b_{abs,c} \,/\, \langle \xi \rangle_c \,, \tag{9}$$

the mean deviation from the field data, i.e.

$$d_{abs,c} = (1/N_c) \sum_i |x_i - \xi_i| \quad \text{and} \quad d_{rel,c} = d_{abs,c} \,/\, \langle \xi \rangle_c \,, \tag{10}$$

[5]This really depends on the cost function which is used. Most cost functions set link speed v to a very low number (but not to zero) at high volumes. Since link costs are proportional to L/v, where L link length, one has that congested links do not contribute much to the cost of a route as long as these links are short and rare. In consequence, much too high volumes can be assigned to such links.

and the root mean square deviation from the field data, i.e.

$$var_c = \left((1/N_c) \sum_i (x_i - \xi_i)^2 \right)^{1/2} \quad \text{and} \quad \sigma_c = var_c \, / \, \langle \xi \rangle_c \, . \tag{11}$$

Links were classified by visual inspection into links leading towards the Portland downtown area, and all other links. The tables show that our simulations are underestimating the flows on the "other" links more than they are underestimating the flows on the links towards downtown. Visual inspection of the simulations reveals that this is probably a result of too *much* demand (and thus congestion) for traffic away from the downtown area. This is what one would expect from our simplifications: We are assuming a spatially homogeneous trip time distribution; yet, one would expect that people who live downtown moved there because they have a higher dislike of long trip times than the average population.

Regarding the size classes, sim-100 systematically underestimates volumes except for class 1 (< 250). Sim-80 underestimates less for class 6 (> 1500), underestimates more for all intermediate classes, and is nearly unbiased for class 1. The interpretation of this is that in sim-100, traffic on the major roads is so congested that the routes are pushed onto the smaller streets. The EMME/2 studies, in contrast, systematically over-estimate volumes. Similar to our results, the ratio of traffic on small vs traffic on large roads is too high. Quite possibly, the fastest path search that is used in both approaches makes simulated travelers accept complicated detours on minor streets more easily than in the real world.

Last, one should also remember that the estimated error of the field counts is assumed to be no better than $\pm 15 - 20\%$. We will come back to this point in the discussion.

In summary, one can say the following: Our simulations are far enough progressed to allow tentative comparisons to real world volume counts. The simulations done for this investigation lead to traffic flows with volumes that are somewhat low when compared to reality. Due to the complexity of the approach, there can be many reasons for this, and the systematic analysis of these effects should be the subject of future research.

7 DISCUSSION

The purpose of this study was to couple a simple demand generation method with route assignment and transportation micro-simulation via a computational feedback procedure. We wanted to explore in how far such an approach is feasible, and then out of scientific curiosity and as a benchmark we compared the results with real world data and with existing EMME/2 study results for the same problem. What can one learn from this?

First, it is now indeed both methodologically and computationally possible to systematically couple demand generation, route selection, and transportation micro-simulation. Again, this does not automatically mean that this is always the best method; however, it can and thus should be explored as one of many alternatives. Also note again that practitioners have always done some version of this feedback: If an assignment did not generate plausible flows, it was common practice to adjust the trip matrix (K. Cervenka, personal communication). The

class	n	mean bias	mean err	RMS err
total	495	-195 (-20%)	342 (36%)	611 (63%)
to-downtown	142	-166 (-15%)	313 (29%)	473 (44%)
other	353	-207 (-23%)	354 (39%)	658 (72%)
< 250	104	46 (32%)	129 (90%)	186 (130%)
$250 - 500$	126	-51 (-14%)	184 (50%)	226 (61%)
$500 - 750$	87	-96 (-15%)	226 (37%)	278 (45%)
$750 - 1000$	44	-184 (-21%)	285 (33%)	367 (43%)
$1000 - 1500$	62	-274 (-23%)	382 (32%)	512 (43%)
> 1500	71	-855 (-25%)	1068 (31%)	1428 (41%)

class	n	mean bias	mean err	RMS err
total	495	-209 (-22%)	344 (36%)	556 (58%)
to-downtown	142	-191 (-18%)	366 (34%)	575 (53%)
other	353	-216 (-24%)	335 (37%)	548 (60%)
< 250	104	2 (1%)	117 (82%)	167 (116%)
$250 - 500$	126	-83 (-23%)	200 (54%)	241 (65%)
$500 - 750$	87	-171 (-28%)	263 (43%)	307 (50%)
$750 - 1000$	44	-212 (-25%)	291 (34%)	370 (43%)
$1000 - 1500$	62	-308 (-26%)	388 (32%)	510 (42%)
> 1500	71	-684 (-20%)	1011 (29%)	1249 (36%)

class	n	mean bias	mean err	RMS err
total	495	83 (9%)	275 (29%)	413 (43%)
to-downtown	142	215 (20%)	318 (29%)	476 (44%)
other	353	30 (3%)	258 (28%)	385 (42%)
< 250	104	84 (59%)	146 (102%)	259 (181%)
$250 - 500$	126	71 (19%)	199 (54%)	263 (71%)
$500 - 750$	87	57 (9%)	212 (34%)	297 (48%)
$750 - 1000$	44	106 (12%)	314 (36%)	376 (44%)
$1000 - 1500$	62	147 (12%)	364 (30%)	473 (39%)
> 1500	71	73 (2%)	574 (16%)	757 (22%)

Table 1: TOP: sim-100. MIDDLE: sim-80. BOTTOM: EMME/2 study.

main differences thus are that we do it systematically and computerized, and that we use a micro-simulation instead of a static assignment. — The second result is that for the morning peak, extremely simple assumptions yield results which are comparable to results of an EMME/2 study.

An important task would be to separate the influences of the different modules. In addition to the input data, there are four computational modules involved in this study: demand generation, routing, traffic flow simulation, and feedback mechanism. All of these can contribute to variations in the volumes. A systematic study would vary or switch these modules one by one and establish the effect on the volumes. This was beyond the scope of this investigation; the following paragraphs will discuss some of the issues.

NETWORK DATA: We have used the same network input data as the EMME/2 studies. Errors here should, to a certain extent, show up similarly with both approaches. It seems that at the level of current accuracy, there are no major errors in these files. That belief is reinforced by the fact that Portland Metro has been using these files for many years.

DEMAND GENERATION INPUT DATA: The data used here was: household locations, workplace locations, and distributions of start times and trip times. The accuracy of these is unkown. With regard to trip times, it was already discussed earlier that the trip times from the census most probably over-estimate times on our network, for two reasons: (1) Travelers intuitively report the time from door to door, not the time actually on the road. (2) Since many local streets are missing in our network, the time spent in our network should be smaller than the complete time on the road. Indeed, reducing all trip times to 80% ("sim-80") in our study did not lead to significant changes in volumes and even led to *higher* (and more realistic) volumes on the major streets, adding to the assumption that reported trip times are probably too high. Also, just looking at home-to-work trips is a simplification. Any traffic besides home-to-work trips is neglected, such as deliveries, people returning from night shifts, shopping, leisure, etc. All these will be indispensable in order to understand 24-hour traffic patterns.

VOLUME COUNT DATA: There is a slight inconsistency between the input data and the volume count data: Input relies on the census, which is from 1990, while the volume counts are from 1992 and 1994. In fact, the average change (mean bias; see above for definition) of traffic flows from 1992 to 1994 is +4%. A bigger challenge is the variability of the data. Fig. 5 shows, where available, the counts from 1992 against the counts from 1994. There is strong variability of the counts, and the average absolute difference (mean error, see above for definition) is in fact 31%.[6] This indicates that in future two things need to be done: (1) Field data need to include a measure of variability; and (2) the corresponding variability measure needs to be obtained from simulations.

ROUTING: This study assumes fastest path routing. Most probably, this is only an approximation of what real people do. In fact, both our simulation results and the model results from the Portland Metro study over-state traffic on minor streets, indicating that the simulated travelers are more willing to accept complicated detours than real world travelers. Also, at the moment no other mode of transportation is included. For the Portland case, this should for example lead to an over-estimation of car traffic between downtown locations.

TRAFFIC FLOW SIMULATION (also called network loading): As discussed earlier, our traffic flow simulation (the queue model) underestimates volumes. In contrast, traditional assignment network loading usually over-estimates volumes (depending on the cost function).

A heuristic possibility for progress would be to design a traffic flow simulation with a behavior somewhere in

[6] This number is larger than one would expect from Fig. 5. The reason is that many high volume streets were not counted in both years, thus leading to a smaller mean, which leads to a larger relative error.

between our queue model and the traditional assignment network loading. A more systematic approach would be to use a more realistic micro-simulation in order to exactly pin-point the deficiencies. In that context, it would be interesting to also look at link speeds in order to decide whether low counts are caused by low traffic or by congestion. This data is easy to extract from the simulations, but it typically does not exist for the field. ITS technology will have a significant impact here.

FEEDBACK: Our feedback method performs slow adaptation based on the previous iteration, similar to fictitious play in game theory. While the result of such an approach is not exactly a Nash Equilibrium, it is assumed to be close.[7] Two aspects need to be considered separately:

- Convergence/uniqueness: If one sees the second-by-second trajectory of the micro-simulation as a point in state space, then the iterations are mappings from that state space into itself (e.g. Bottom, 2000). The way our iterations are set up, they describe a Markov-process in that state space, which means that the iterations eventually reach a steady state with a corresponding steady state density in state space (e.g. Cantarella and Cascetta, 1995). Little is known about the characteristics of this steady state density distribution, for example if it is unique, or how many iterations one would need to be reasonably close to ergodicity. In practice, it seems that route iterations behave in a similar way as traditional steady state assignment, that is, they normally yield, within Gaussian fluctuations, unique results for the traffic on the link level (e.g. Bottom, personal communication; Nagel et al, 1999). We are not aware of results of how this extends to feedback iterations into the trip distribution as considered in this paper.
- Human behavior: It is well-known that convergence results are used only because they are scientifically well-defined, not because they are realistic. When comparing to field data, one should keep in mind that it is unclear how close real systems are to the converged result.

INHOMOGENEITIES: One aspect already mentioned earlier in the text but that should be stressed again is that our method unrealistically assumes homogeneity of all aspects of the scenario except for traffic. For example, it is assumed that the behavioral function f_{ch} is the same for everybody, and that one can obtain it by averaging both the trip times and the accessibility over the whole population and the whole region. This is clearly a simplifying assumption — for example, one might expect that people living downtown have a stronger dislike of long trip times than the average population.

Another inhomogeneity in the Portland situation stems from the fact that the part of the metro region which is north of the Columbia river, so-called Clark County, is part of the State of Washington, while the rest of Portland is part of the State of Oregon. Many Oregon workers choose to live in Clark County for the lower property taxes and cheaper large-lot housing (an effect of differences in land use policy), despite the congested commute and Oregon income tax. Oregon has one of the highest personal income taxes of the U.S. States, while Washington does not have a State tax on personal income. Oregon personal income tax is also paid by non-Oregon residents as long as they work in Oregon. Thus, there is a substantial tax incentive for those who live in Clark County to also work there. This, however, is often not possible due to a low jobs-housing ratio

[7] For certain –much simpler– systems, one can show that many plausible iteration schemes converge towards the same state (Hofbauer and Sigmund, 1998).

in Clark County. All this results in a relatively high split between peak and non-peak direction volumes on the Columbia River bridges. Sales tax is the opposite: There is no sales tax in Oregon while sales taxes in Clark county average 8%. In consequence, retail activity in Clark County is somewhat suppressed by residents' proximity to tax-free shopping in Oregon. For example, there is a major big-box retail area on the Oregon side of the I-5 bridge that owes its existence to the sales tax disparity. (Bill Stein, Portland Metro, personal communication)

This should result in less traffic northbound into Clark county in the morning peak in reality than in our model. This is easy to check since there are only two bridges across the Columbia river. Indeed, with sim-80 we obtain 7473 veh/hour northbound as opposed to 4650 in the field, while southbound the numbers are comparable: 10052 and 9740, respectively. Sim-100 numbers are lower than sim-80 numbers, due to congestion in the model, but have the same tendency.

8 SUMMARY

We have implemented a computational feedback between demand generation and traffic simulation in a real world setting in Portland/Oregon. This was done via a double relaxation loop: an inner loop for relaxation of the route assignment with fixed demand, and an outer loop for relaxation of the demand. Typically, about 70 runs of the traffic micro-simulation are necessary for one relaxed result. We have used data from Portland/Oregon.

For simplicity, we have concentrated on assigning workplaces to workers (whose home locations were given). The challenge was to perform this workplace assignment self-consistently such that the resulting trip times correspond to the trip time distribution given via census data.

Our results demonstrate that with current computational technology and simple models, it is possible to do such studies while retaining microscopic resolution throughout the whole computation. Microscopic resolution here means that each of the about 500 000 travelers and each vehicle are represented individually in each step of the method. Our simulations were run on single CPU workstations; one relaxation series typically took about four days of computer time.

Because of the many simplifications, we did not expect our results to be a good model of reality. Nevertheless, in order to provide a benchmark we compared our results to real world morning peak volume counts from the Portland/Oregon area, and we included into the comparison results of an older study by Portland Metro using different methods. These results are summarized in Fig. 4. It is encouraging that one gets so close with so relatively little investment in terms of input data. In fact, input data consists of nothing more but the EMME/2 street network information, some population characteristics from the census (home locations of workers; overall trip time distribution for home-to-work trips; overall trip starting time distribution), and the locations of workplaces. The methodology uses a relaxation algorithm of workplace assignment, a fastest-path routing, and a queuing micro-simulation. Our study demonstrates that such a microscopic approach is both computationally and methodologically feasible even on modest computing hardware.

9 ACKNOWLEDGMENTS

We are extremely grateful to B. Stein, D. Walker, K. Lawton, and others at Portland Metro for providing the data for the Portland/Oregon area, without which this study would not have been possible at all. Much of the work was done while the authors were at Los Alamos National Laboratory (LANL) and at Santa Fe Institute (SFI). We thank the TRANSIMS project at LANL for providing the technical infrastructure necessary for running these studies.

References

Arentze, T., Hofmann, F., Joh, C., and Timmermans, H. (1998). Experiences with developing ALBATROSS: A learning-based transportation oriented simulation system. In: *Verkehr und Mobilität*, no. 66 in Stadt Region Land, pp. 61–70. Institut für Stadtbauwesen, Technical University, Aachen, Germany.

Axhausen, K. (1990). A simultaneous simulation of activity chains. In: *New Approaches in Dynamic and Activity-based Approaches to Travel Analysis* (P. Jones, ed.), pp. 206–225. Avebury, Aldershot.

Babin, A., Florian, M., James-Lefebvre, L., and Spiess, H. (1982). EMME/2: Interactive graphic method for road and transit planning. *Transportation Research Record*, **866**, 1–9.

Beckman, R. J., Baggerly, K. A., and McKay, M. D. (1996). Creating synthetic base-line populations. *Transportion Research Part A – Policy and Practice*, **30**, 415–429.

Ben-Akiva, M. and Lerman, S. R. (1985). *Discrete choice analysis*. The MIT Press, Cambridge, MA.

Bottom, J. (2000). *Consistent anticipatory route guidance*. Ph.D. thesis, Massachusetts Institute of Technology, Cambridge, MA.

Bowman, J. L. (1998). *The day activity schedule approach to travel demand analysis*. Ph.D. thesis, Massachusetts Institute of Technology, Cambridge, MA.

Cameron, G. D. B. and Duncan, C. I. D. (1996). PARAMICS — Parallel microscopic simulation of road traffic. *J. Supercomputing*, **10(1)**, 25.

Cantarella, C. and Cascetta, E. (1995). Dynamic process and equilibrium in transportation network: Towards a unifying theory. *Transportation Science A*, **25**, 305–329.

Cascetta, E. and Papola, A. (1998). An implicit availability/perception random utility model for path choice. In: *Proceedings of TRISTAN III*, vol. 2. San Juan, Puerto Rico.

Chabini, I. (1998). Discrete dynamic shortest path problems in transportation applications: Complexity and algorithms with optimal run time. *Transportation Research Records*, **1645**, 170–175.

Doherty, S. T. and Axhausen, K. W. (1998). The developement of a unified modelling framework for the household activity-travel scheduling process. In: *Verkehr und Mobilität*, no. 66 in Stadt Region Land. Institut für Stadtbauwesen, Technical University, Aachen, Germany.

DYNAMIT (since 1999). Massachusetts Institute of Technology, Cambridge, Massachusetts. See its.mit.edu.

Esser, J. (1998). *Simulation von Stadtverkehr auf der Basis zellularer Automaten*. Ph.D. thesis, University of Duisburg, Germany. See also www.traffic.uni-duisburg.de.

Esser, J. and Nagel, K. (1999). Census-based travel demand generation for transportation simulations. In: *Traffic and Mobility: Simulation – Economics – Environment* (W. Brilon, F. Huber, M. Schreckenberg, and H. Wallentowitz, eds.), pp. 135–148. Aachen, Germany.

Gawron, C. (1998). *Simulation-based traffic assignment*. Ph.D. thesis, University of Cologne, Germany.

Hofbauer, J. and Sigmund, K. (1998). *Evolutionary games and replicator dynamics*. Cambridge University Press.

Jacob, R. R., Marathe, M. V., and Nagel, K. (1999). A computational study of routing algorithms for realistic transportation networks. *ACM Journal of Experimental Algorithms*, **4**.

Kelly, T. (1997). Driver strategy and traffic system performance. *Physica A*, **235**, 407.

Mahmassani, H., Hu, T., and Jayakrishnan, R. (1995). Dynamic traffic assignment and simulation for advanced network informatics (DYNASMART). In: *Urban traffic networks: Dynamic flow modeling and control* (N. Gartner and G. Improta, eds.). Springer, Berlin/New York.

Metaxatos, P., Boyce, D., Florian, M., and Constantin, I. (1995). Implementing combined model of origin-destination and route choice in EMME/2 system. *Transportation Research Records*, **1493**, 57–63.

Nagel, K. and Barrett, C. (1997). Using microsimulation feedback for trip adaptation for realistic traffic in Dallas. *International Journal of Modern Physics C*, **8**, 505–526.

Nagel, K. and Rasmussen, S. (1994). Traffic at the edge of chaos. In: *Artificial Life IV: Proceedings of the Fourth International Workshop on the Synthesis and Simulation of Living Systems* (R. A. Brooks and P. Maes, eds.), pp. 222–235. MIT Press, Cambridge, MA.

Nagel, K., Rickert, M., Simon, P. M., and Pieck, M. (2000). The dynamics of iterated transportation simulations. See www.arXiv.org, nlin.AO/0002040. Earlier version in: Proceedings of 3rd TRIannual Symposium on Transportation ANalysis (TRISTAN-III) 1998 in San Juan, Puerto Rico.

Rakha, H. A. and Van Aerde, M. W. (1996). Comparison of simulation modules of TRANSYT and INTEGRATION models. *Transportation Research Record*, **1566**, 1–7.

Rickert, M. (1998). *Traffic simulation on distributed memory computers*. Ph.D. thesis, University of Cologne, Germany. See www.zpr.uni-koeln.de/˜mr/dissertation.

Schwerdtfeger, T. (1987). *Makroskopisches Simulationsmodell für Schnellstraßennetze mit Berücksichtigung von Einzelfahrzeugen (DYNEMO)*. Ph.D. thesis, University of Karsruhe, Germany.

Sheffi, Y. (1985). *Urban transportation networks: Equilibrium analysis with mathematical programming methods*. Prentice-Hall, Englewood Cliffs, NJ, USA.

Simon, P. M. and Nagel, K. (1999). Simple queueing model applied to the city of Portland. *International Journal of Modern Physics C*, **10**, 941–960.

TRANSIMS (since 1992). TRansportation ANalysis and SIMulation System. Los Alamos National Laboratory, Los Alamos, NM. See transims.tsasa.lanl.gov.

Planung Transport und Verkehr (PTV) GmbH. See www.ptv.de.

Wagner, P. and Nagel, K. (1999). Microscopic modeling of travel demand: Approaching the home-to-work problem. Paper 99 09 19, Transportation Research Board Annual Meeting, Washington, D.C.

Yang, Q. (1997). *A Simulation Laboratory for Evaluation of Dynamic Traffic Management Systems*. Ph.D. thesis, Massachusetts Institute of Technology. See also its.mit.edu.

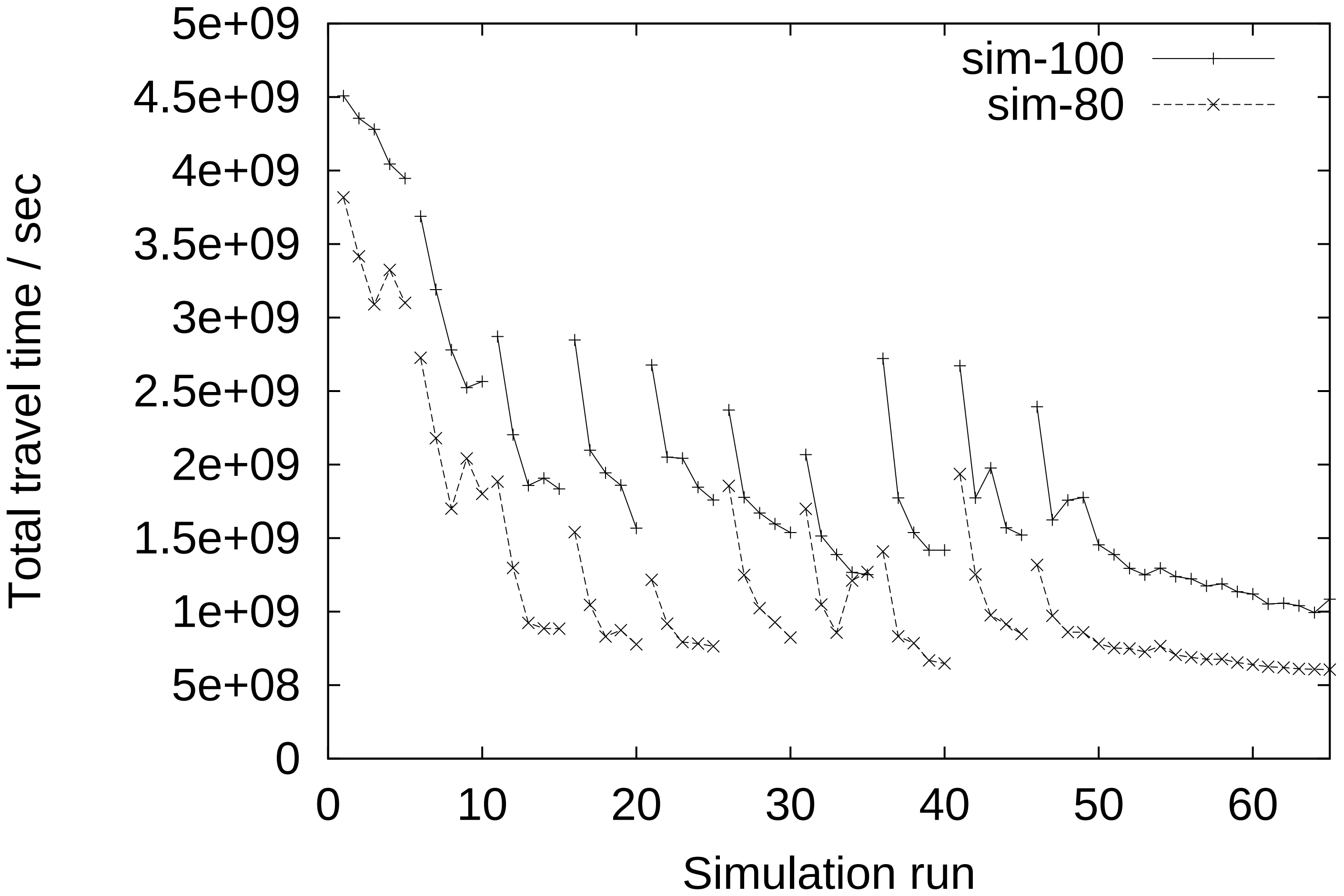

Figure 2: Total trip time in the simulation during the iterative assignment with the original census trip time distribution (sim-100) and the census distribution with trip times reduced to 80% (sim-80).

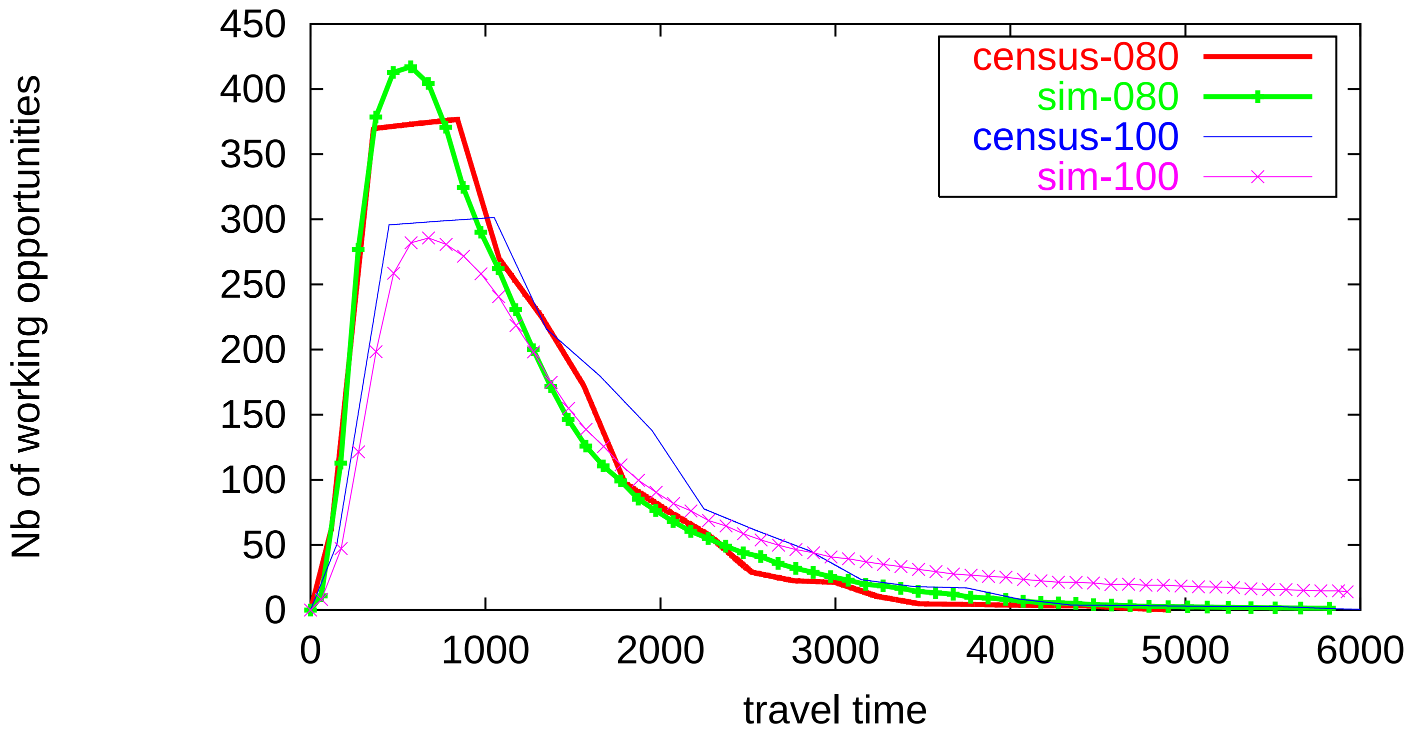

Figure 3: Trip time distributions in the queuing simulation at the 70th iteration in comparison to the 100% and the 80% census trip time distribution. Only completed trips contribute to the distribution.

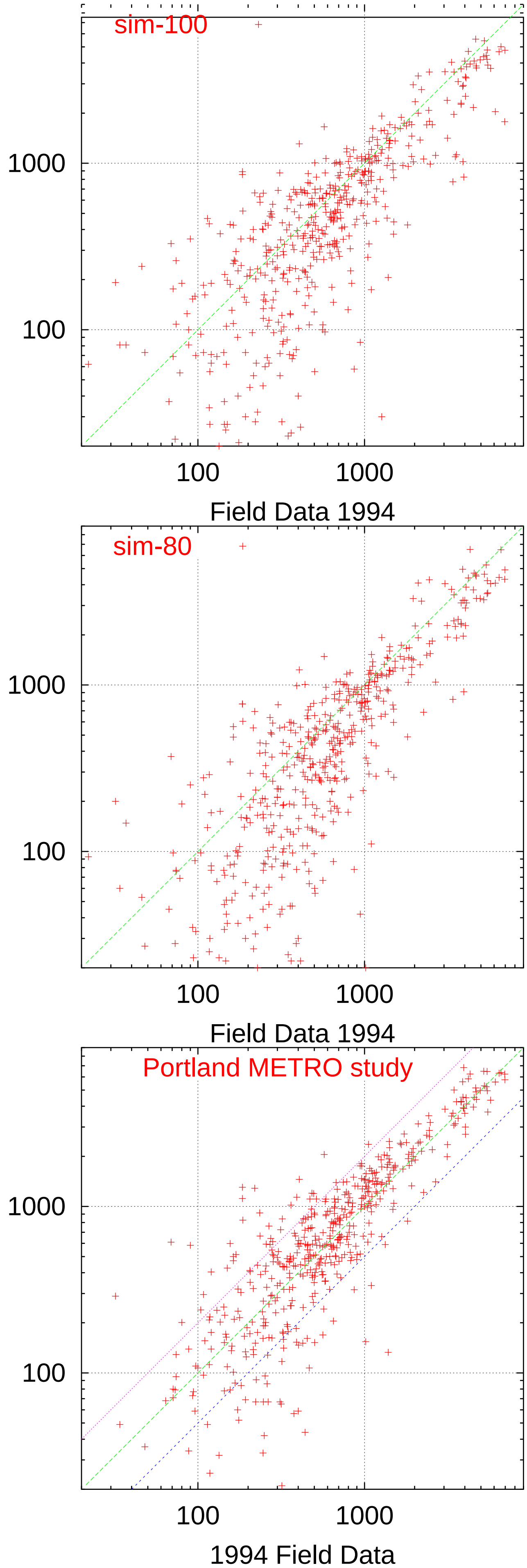

Figure 4: Scatterplot of simulated data (y-axis) vs. field data (x-axis). TOP: sim-100. CENTER: sim-80. BOTTOM: EMME/2-study. It is remarkable that reducing the desired trip times by 20% (top to middle) does not seem to change very much at all.

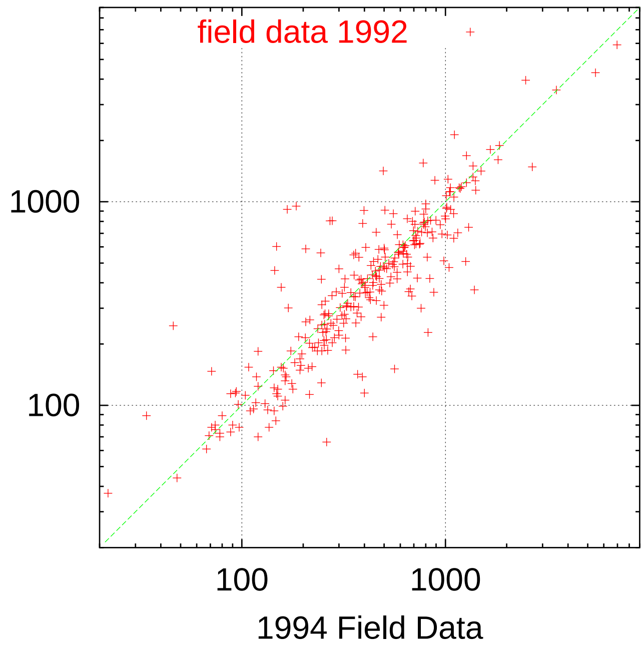

Figure 5: Variability of field data. For some measurement locations, count data were available both for 1994 and 1992. For those locations, the 1992 value is plotted against the 1994 value. A better understanding of field data variability will be necessary for further progress.