Simplified cellular automaton model for city traffic

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We systematically investigate the effect of blockage sites in a cellular automaton model for traffic flow. Different scheduling schemes for the blockage sites are considered. None of them returns a linear relationship between the fraction of ''green'' time and the throughput. We use this information for a fast implementation of a simulation of traffic in Dallas. [S1063-651X(98)14506-3]

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I. INTRODUCTION

In today's crowded world, space and money to build transportation systems that can fulfill all demands is often not available, or it is not desired to spend it on transportation system infrastructure. The result is congestion: from congested urban centers to congested inner-city corridors to congested railways and congested airports. In consequence, some ''forecasting'' tool would be desirable. Unfortunately, congestion has the side effect that causal relations become much more spread both spatially and temporally [1]. If a road is crowded, a person may attempt a different route or a different mode (spatial spreading), or she may attempt the trip at a different time (temporal spreading) or even totally drop the trip. The result is that planning tools need to consider a much wider spatial and temporal context than ever before. Conceptually this means that for such problems the method needs to be ''activity based,'' i.e., one needs to consider the whole process of how people plan transportation in a daily, or, better, weekly context (see, e.g., [2]).

Another effect of being in the congested regime is that one needs to worry a lot more than before about having a *dynamically* correct representation of the transportation system: For example, a peak-period spreading of traffic will not show up if one models traffic averaged over 24 hours, as many traditional tools do. Thus, we are suddenly faced with a problem where we need to introduce more dynamical correctness into the modeling while at the same time considering much wider temporal and spatial scales than before.

It is fairly obvious that, when faced with a dynamical problem, a ''microscopic'' approach, i.e., starting with a description of the smallest particles, is in terms of methodology the cleanest one. In transportation science, this currently means to consider individual travelers rather than, say, aggregated link flows. For example, it is difficult to include individual route choice behavior into a simulation that does not resolve individual drivers. There is also some agreement that the currently most straightforward method to deal with microscopic approaches in complicated real-world contexts is computer simulation, as opposed to analytical techniques. Now, when faced with a computationally intensive problem, such as systematic scenario evaluations (see, e.g., [3–5]), or the simulation of the whole national transportation system [6], a very detailed and realistic microsimulation (see, e.g., [7,8]) may be computationally too slow, or too data-intensive to run.

Alternatives here are simplified models that still capture the essentials of the dynamics at the transition to the congested regime. Since traffic in general is dominated by the bottlenecks in the system, these simulations concentrate on exactly these bottlenecks. The most important bottlenecks in urban systems are traffic lights. The natural outcome of this way of thinking are queuing-type models [9–11]. For vehicles that enter the link, one calculates when they could arrive at the end of the link. When that time is reached in the simulation, they are added to a queue at the end of the link. They leave the queue once they have advanced to its beginning. The queue may have a limited service rate, which models capacity restrictions.

This paper approaches this problem from a slightly different angle. We use a very simple single-lane microsimulation to capture at least some of the dynamics that is going on on the link itself (see also [12]). This paper will provide a systematic approach to such a model. Section II will describe our model, the way capacity restrictions are modeled, what their behavior is, and what that means for the relation between the simulation and reality. In fact, capacity restrictions are simply modeled by ''impurity sites'' or temporary ''blockages'' (e.g., [13]). Section III discusses an implementation and some results for a Dallas study. This is followed by a short discussion, highlighting the differences between our approach and other ''queuing-type'' approaches (Sec. IV), and a summary.

II. A SIMPLIFIED APPROACH

We present a simple simulation model of city traffic, using a combination of stochastic cellular automata (CA) and stochastic transitions between streets. To represent the city network, we use the usual definition (e.g., [14]) for links and nodes: a link is a directed street segment, such as a bidirectional road divided into two links, whereas a node is an intersection; a link can also be defined by an input node and an output node. Vehicles are moved on a simple single-lane CA link, and are transferred from link to link following a simple stochastic law based on the link's capacity.

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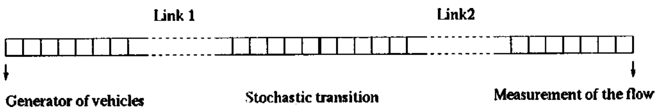

FIG. 1. Schema of the experiment.

A. Links

Links have different characteristics including length, speed limit, number of lanes, maximum capacity, etc. The length is necessary to adjust the number of sites needed for the discrete approach of the CA. We use the standard reference of 7.5 m for the length of one site [14,8,15]. Each site can be empty, or occupied by a vehicle with an integer velocity $v \in \{0 \ldots v_{max}\}$. $v_{max}=5$ gives good agreement with field measurements.

Since each link is considered as a one-lane segment, vehicles are moved using the rules of Refs. [16,15]. Summarizing the one-lane CA model, the variable *gap* gives the number of unoccupied sites in front of a vehicle. p_{noise} is the probability with which the vehicle is slowed down by one unit, and *rand* is a random number between zero and one. One iteration consists of the following three sequential steps which are applied in parallel to all cars: (1) acceleration of free vehicles, IF $(v<v_{max})$ THEN $v=v+1$; (2) slowing down due to other cars, IF $(v>gap)$ THEN $v=gap$; (3) stochastic driver behavior, IF $(v>0)$ AND (rand $<p_{noise}$) THEN $v=v-1$.

B. Stochastic transitions

We introduce various stochastic models to differentiate the existing links within a city, from high capacity segments such as freeways to low capacity segments such as arterials. If we consider only one-lane links, the stochastic transition is introduced to control the output flow of a link. A high capacity link will produce a high output flow, while a low capacity link will produce a low output flow.

1. Random traffic light

Let us consider the experiment in Fig. 1, consisting of two consecutive links separated by a transition probability p_{trans}. The first site of link 1 operates as a generator of vehicles, where one vehicle is introduced per n iteration(s). The flow measured at the end of the second link versus the number of iterations is shown in Fig. 2. The transition probability is set to 0.5 in this example. The flow measured at iteration t is the number of vehicles that left the second link until that moment, divided by t. As a result, the unity of the flow is vehicle per iteration. Commonly, one iteration is taken to correspond to 1 sec of real time [15,17]; a flow of one vehicle per iteration would thus correspond to one vehicle per second, or 3600 vehicles per hour. [18]

We introduce one vehicle every three iterations at the first site of the first link with maximum velocity 5. This is enough to assure that the first link will reach a flow of around 0.33 vehicles per iteration (1200 veh/h) for a p_{noise} of 0.5, which is close to the maximum throughput of such a link in the CA implementation [15]. If the first site is not empty at the introducing time step, we do not add a vehicle. The vehicle's velocities are updated by the one-lane CA model before reaching the intersection. If the vehicle is allowed to go

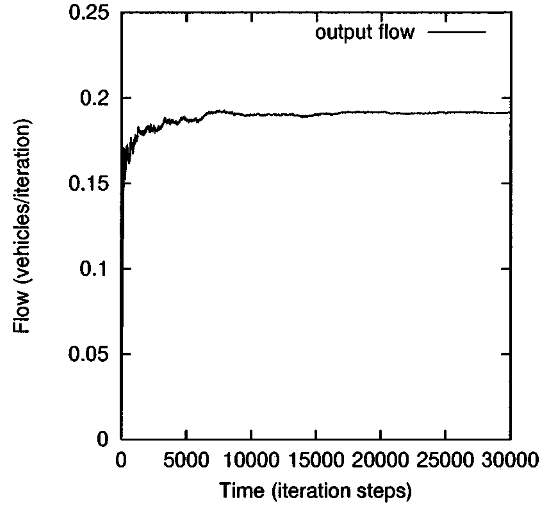

FIG. 2. Flow vs time for a transition probability, p_{trans}, of 0.5.

through the intersection by the CA forward rule, we check the transition probability.

If the generated random number is lower than the probability p_{trans}, the vehicle keeps its velocity and reaches the second link. In contrast, if the random number is greater than p_{trans}, we place a virtual car in the first site of the second link in order to force the vehicle to brake and stop at the intersection. When the light ''turns green,'' this virtual car is removed again. Technically: If a car reaches the last five sites of a link, it produces a random number. We introduce the simple algorithm

1. Transition check: IF (rand$<p_{trans}$) THEN normal CA-update ELSE gap=distance from the vehicle to the intersection.

This situation is, in principle, well understood. The ''impurity site'' will create a reduced flow that can pass that site, and since flow needs to be conserved along the link, this sets the maximum throughput for the link [13,19–22]. Yet, in the context of the stochastic traffic cellular automaton as used here, we are only aware of Ref. [23]. That paper implements a hindrance by setting the maximum velocity of a certain number h of consecutive cells to INT(v_{max}/2), where INT( ) takes the integer value. Different throughputs can then be obtained by using different values for h. That mechanism seems more suited for modeling capacity reduction in construction sites than for modeling capacity reduction by traffic lights. For example, speed and capacity are, in principle, unrelated, so that it does not seem a good idea to model capacity via artificial speed limits. Also, since h is discrete, capacity in Ref. [23] can only be changed in coarse-grained steps, a feature that is undesirable for our purposes.

Figures 3–5 demonstrate the formation of traffic jams spreading to the beginning of the link, caused by braking of vehicles. The beginning of the second link can again be considered as a generator of vehicles. Nevertheless, the input flow to that second link and p_{trans} are not proportional.

To illustrate this comment, we vary the transition probabilities from zero to one. The average flow obtained for each experiment is presented in Fig. 6. For each data point, the flow is averaged in the time period (15 000,30 000), see

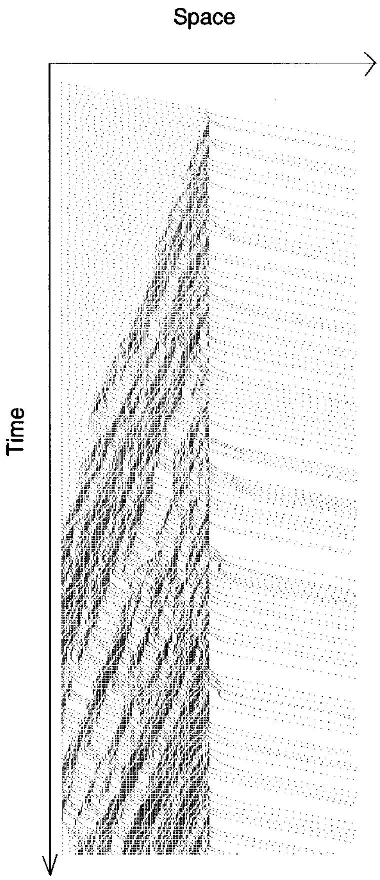

FIG. 3. Space-time diagram for a transition probability, p_{trans}, of 0.5.

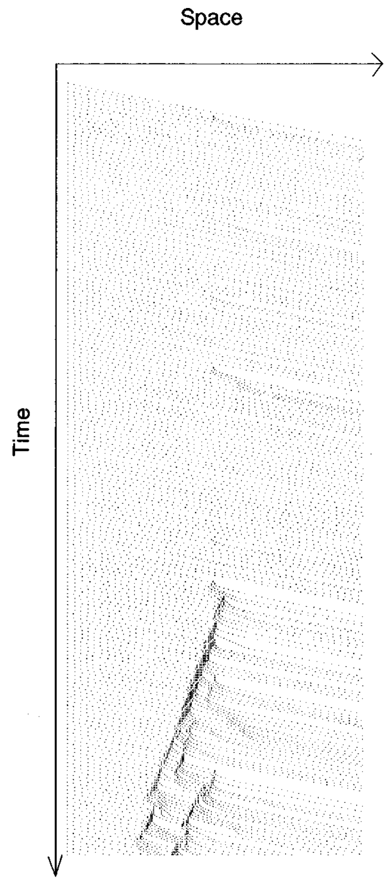

FIG. 4. Space-time diagram for $p_{trans}=0.9$.

Fig. 2. The intersection does not function as a perfect generator of service rate p_{trans}. If a vehicle leaves the last site of the first link, this vehicle is not automatically replaced, due to the stochastic third step included in the one-lane CA model. The plot of Fig. 6 can be divided into three different parts:

(i) A high transition probability (p_{trans} between 0.8 and 1.0) gives linear results with the output flow. In this scenario, vehicles do not stop often at the intersection, thus the intersection does not work like a stop and start point. See Fig. 4.

(ii) A low transition probability (between 0 and 0.4) gives results that can be explained by a simple hypothesis. Most of the cars stop at the intersection and form a compact traffic jam, as shown in Fig. 5. There are no important spaces in this queue. Assuming that the second to last site of the first link is always crowded, how many iterations does a vehicle need to go through the intersection? If a vehicle is on the last site of link 1, the vehicle needs $1/p_{noise}$ iterations on average to advance, and then multiplied by $1/p_{trans}$ to go through the intersection. Viewed from the perspective of the next following vehicle, that one needs to wait $1/p_{noise}\times 1/p_{trans}$ steps until the vehicle ahead is gone, and then another $1/p_{noise}$ steps to move itself to arrive at the last site. As a result the average number of iterations for a vehicle to advance from the second last site of link 1 to the intersection is $1/p_{noise} + 1/(p_{noise}p_{trans})$. This could in theory be continued, but it would not necessarily get better because one would need to include the influence of ''holes'' in the queue; or, more technically: The approximation is only valid for $p_{trans}\rightarrow 0$, and second-order corrections are thus negligible. In any case, the corresponding flow is $F\approx p_{noise}p_{trans}/(1+p_{trans})$. Using $p_{noise}=0.5$ plus that one iteration corresponds to one second and converting everything to hourly flows (i.e., multiplying by 3600), one obtains

$$F[\text{veh/h}]\approx 1800\,\frac{p_{trans}}{1+p_{trans}}.$$

The function F shown in Fig. 6 fits well to the data measured for low values of p, while for $p\geqslant 0.4$ the hypothesis is no longer valid.

(iii) Figure 3 demonstrates what happens for transition probabilities between 0.4 and 0.8 at a microscopic level. Within the queue, holes are generated by the intersection and an analytical approach becomes more difficult. Periodically, vehicles pass through the intersection without braking and stopping, which produces a higher flow compared to the linear relationship illustrated in Fig. 6.

2. Other traffic lights

Many experiments can be conducted using other probability distributions for the intersection. The model previously described operates like a random traffic light, where the light becomes green with the probability p_{trans}, which is also the fraction of the time the light is green: $f_{green}=p_{trans}$. That model can be considered to be one between two extreme distributions, where in between the extreme cases one can encounter an infinite number of distributions that keep the

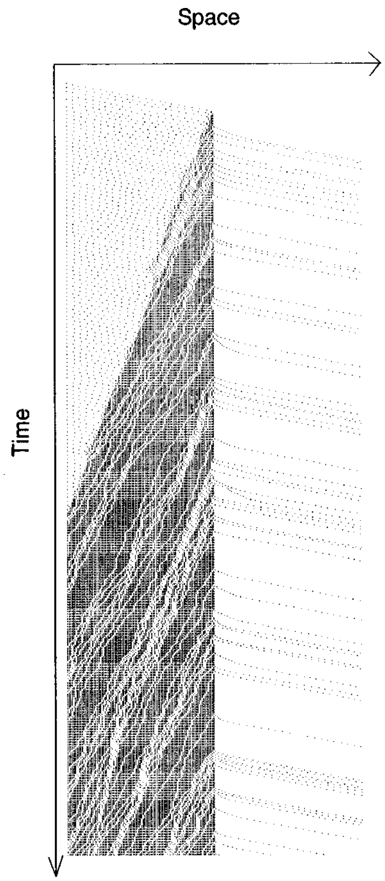

FIG. 5. Space-time diagram for $p_{trans}=0.2$.

fraction of a green light of the total time of a traffic cycle the same. (i) The first distribution is a normal traffic light. The green fraction here is straightforward: $f_{green}=T_{green}/(T_{green}+T_{red})$. (ii) We call the second model a Dirac traffic light. As we work with discrete systems, the objective is to set a green light or a red light on only one time unit, equally spaced on a cycle. The green fraction is $f_{green}=1/(1+T_{red})$ for $T_{red}\geq 1$ (and $T_{green}=1$ by definition) or $1-1/(1+T_{green})$ for $T_{green}\geq 1$.

All three distributions are illustrated in Fig. 7. In the following, we present the same experiments discussed above, for these two distributions.

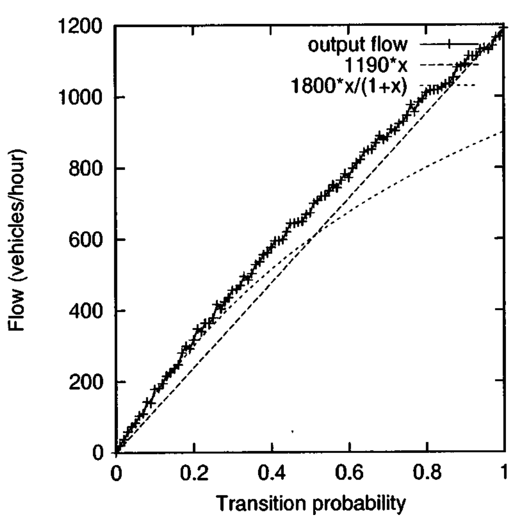

FIG. 6. Flow vs transition probability, p_{trans}.

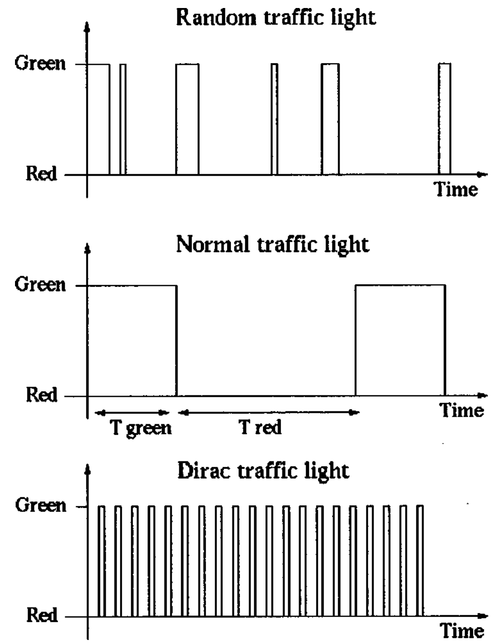

FIG. 7. Different ways to distribute green times.

3. Normal traffic light

We first repeat the same experiment described in Fig. 1 with a normal traffic light at the intersection. The dissolution of a queue as the light turns periodically green is shown in Fig. 8. This phenomenon does not provide an easy analytical solution. For each green fraction f_{green} ranging from 0 to 1, the input flow of the second link is measured and is illustrated in Fig. 9. This relationship is almost linear. Even for high values of the green fraction, vehicles still have to stop occasionally, which decreases the output flow. Figure 10, when compared to the space-time diagram produced by the random traffic light for the same value of f_{green} (Fig. 4), displays a lack of fluidity.

4. Dirac traffic light

The Dirac traffic light generates the highest flow for a given f_{green} in the experiment of Fig. 1. The space-time diagram performed with a green time fraction of $f_{green}=0.5$ is given as an example. In this case, the Dirac traffic light is successively green and red. Figure 11 shows less compact traffic jams at the end of the first link than the other space-time diagrams for the same fraction of green time. This is still due to the vehicles that pass through the intersection at maximum velocity without braking. The analytic explanation for this is the fact that the parallel update of the CA tends to generate states where particles are followed by holes, sometimes called ''particle-hole attraction'' [24].

The output flow of link 1 for any value of f_{green} is much higher than the two flows measured previously for the two other probability distributions. There is no linear relation at any position on this diagram. The space-time diagrams plotted for a $f_{green}=0.16$ and $f_{green}=0.9$ exhibit more fluidity for the output traffic (Figs. 12–14).

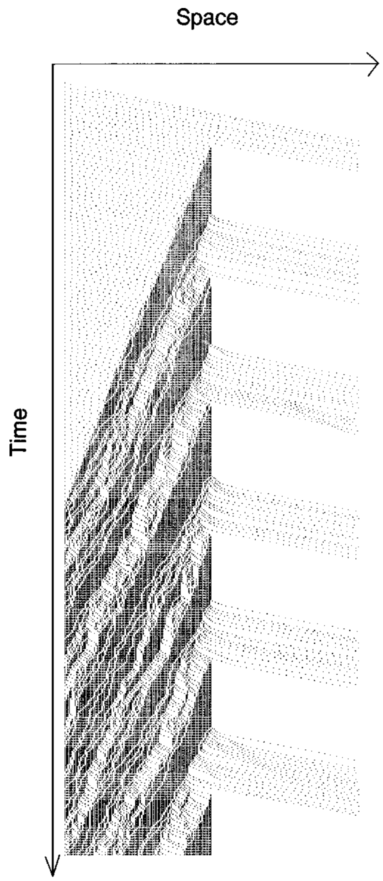

FIG. 8. Space-time diagram for normal traffic light, $f_{green} = 0.5$.

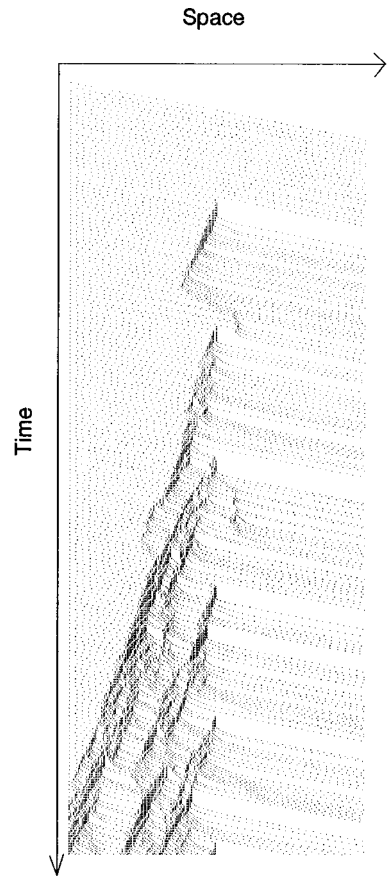

FIG. 10. Space-time diagram for normal traffic light, $f_{green} = 0.9$.

III. DALLAS

A. Implementation

The normal traffic light model is the most linear model simulated in this paper. On the other hand, setting a traffic light at each intersection would cost some computation time and coding overhead. The random traffic light presents the advantage to be checked only when a vehicle reaches the intersection. The vehicle generates a random number that allows it to drive through the intersection or not.

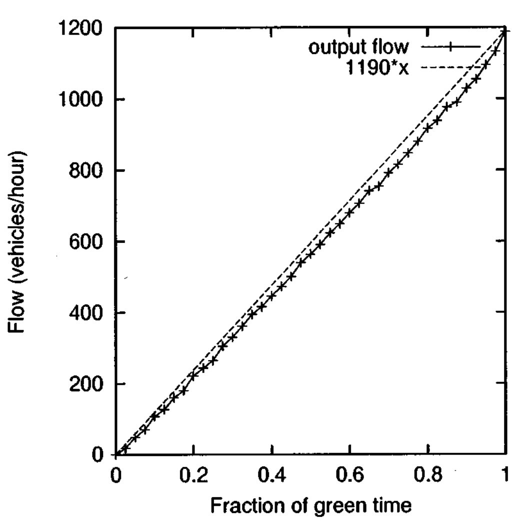

FIG. 9. Flow vs fraction of green time, f_{green}, for normal traffic light.

We apply this model to the Dallas–Fort Worth area. The context is the so-called Dallas-Fort Worth case study [4,25] which has been done as part of the TRANSIMS (TRansportation ANalysis and SIMulation System) project [2]. TRANSIMS uses individual route plans for each individual traveler. A route plan consists of a starting time, a starting location, a list of links the vehicle intends to follow, and an ending location. A microsimulation in the TRANSIMS project such as the one described here is thus faced with the task to move these vehicles according to these specifications.

One immediately observes that one somehow has to correct for the fact that we are only using single-lane roads, that is, our links will usually not be able to carry the prescribed number of vehicles. We solve that problem by using a sub-sample of the plans. The size of that sub-sample is obtained as follows: (i) $p_{noise} = 0.5$ results in a maximum throughput of a link of approximately 1200 veh/h (using $p_{trans} = 1$). (ii) We search for the link with the highest capacity in the area we want to simulate. In our case, this was a four lane freeway with a capacity of 7800 veh/h. (iii) We thus need to sub-sample the population by a factor of 1200/7800≈0.154, i.e., a route plan from the full plan-set is going to be used with a probability of 0.154. (iv) Links which have a lower capacity than 7800 veh/h take this fact into account by using a value of p_{trans} according to Fig. 6, i.e., if the value of the road is C, then the value $C0.154$ is used on the y axis to find the correct value of p_{trans} on the x axis.

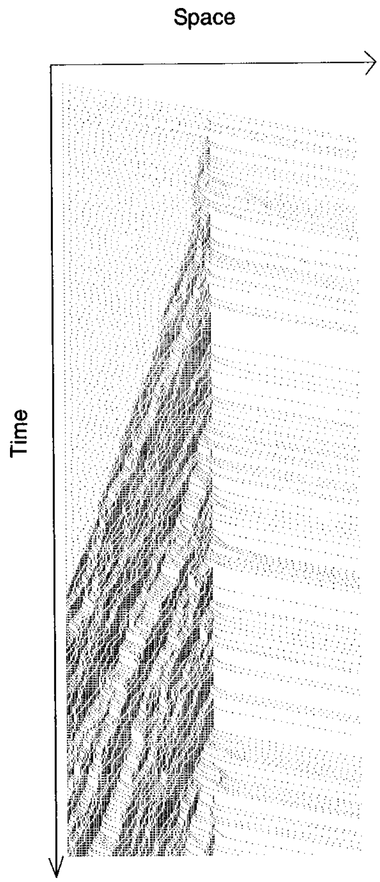

FIG. 11. Space-time diagram for Dirac traffic light, $f_{green}=0.5$.

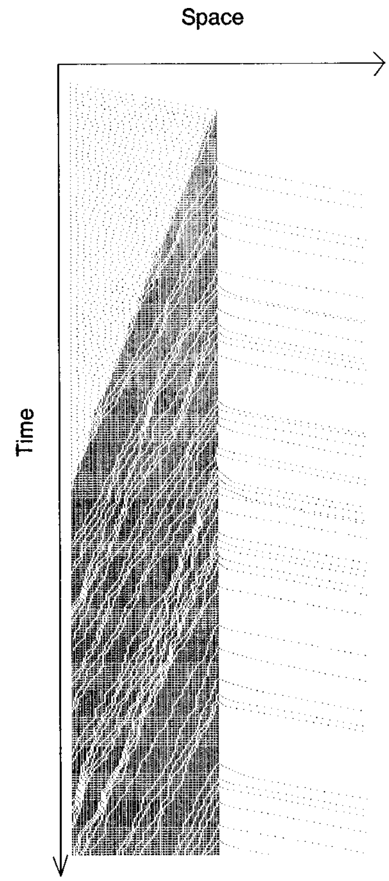

FIG. 12. Space-time diagram for Dirac traffic light, $f_{green}=0.16$.

A more precise calibration is more complicated than this because it also depends on the interplay between route planning and route execution. This is beyond the scope of this paper; further publications on the subject are in preparation.

B. Simulation results

In this section, we want to give some examples of how this simulation is going to be used. These examples will be given in the context of the TRANSIMS Dallas–Fort Worth case study. That case study used as input a street network of the Dallas–Fort Worth area, containing 24662 unidirectional links and 9864 nodes, and information on all trips in this area during a 24 hour period (approx. 10 million trips). The study focused on a busy 5×5 mile area north of downtown Dallas, and on the time between 5 am and 10 am. This still involved 300 000 trips. As mentioned above, microsimulations in the TRANSIMS project are route-plan driven. Thus, for each of these 300 000 trips, route plans were calculated. The fact that drivers adjust to congestion caused by other drivers was taken into account by iterating several times between the route planning and the microsimulation. For further information, see Refs. [25–27].

One important specification missing in the above description of the microsimulation is how vehicles enter and leave the simulation. TRANSIMS specifies parking locations along links, which represent all parking opportunities that can be reached from this link. In order to prevent that the traffic that leaves parking unrealistically disturbs the traffic flow, vehicles from the parking locations are only inserted if v_{max} sites backwards from the parking location are empty. If the space is not free, the car is placed in a queue, waiting to enter the simulation in one of the following iterations.

A snapshot of such a simulation with the model described in this paper can be found in Fig. 15. The denser square area in the center represents the study area, where all streets including local streets were represented in the data base. For this example, the streets outside that area were also simulated. Dots denote individual vehicles. In this plot, most of the traffic is on the freeways, as is realistic. Also, one notes that for lower capacity road, traffic is mostly queued up towards the end, as one would expect from the dynamics of the model. Yet, this is really not too unrealistic since also in reality traffic through minor roads tends to queue up at the ends.

The space-time diagram of five consecutive links is shown in Fig. 16. These links are a part of an east-west arterial located in the north of the study area. The figure shows nicely how queues build up at the end of links due to the capacity restrictions.

As a further example, we present the travel time versus departure time for each vehicle (Fig. 17). This figure shows that even such a simple simulation as the one described in this paper can, given a realistic trip demand input, display the higher travel times during the rush hour.

In general, a main advantage of doing a microscopic simulation (i.e., representing individual travelers) is, besides

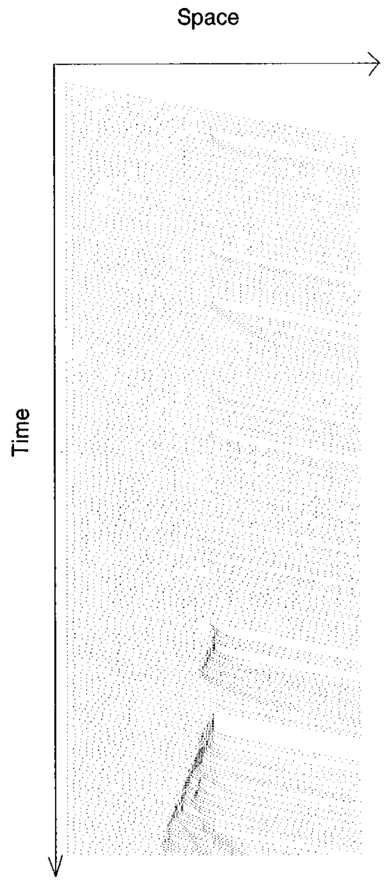

FIG. 13. Space-time diagram for Dirac traffic light, $f_{green} = 0.9$.

having a more realistic dynamics than many traditional approaches, that one can extract information that relates to individuals. For example, one can extract accessibility information for certain areas, and one can differentiate this information by demographic characteristics, say, income or race. Accessibility deals with questions such as how difficult it is to reach, say, workplaces from a certain residential area, how this depends on car ownership, etc. This becomes increasingly important in societies that undertake significant efforts to target public money and effort to certain demographic groups. As another example, one could find out from the simulation who is waiting before a bottleneck, where these persons come from and go to, and (again) what their demographic characteristics are. Building a public transit system to relieve the bottleneck will only be successful if it is actually an alternative for the people waiting at the bottleneck.

C. Computational performance

We present a performance diagram in Fig. 18, where we introduce the RTR versus the simulation time. The RTR is the ratio of the real time on the simulation time. This example of simulation was executed on a SUN UltraSparc CPU with 250 MHz where approximately 46 000 plans were simulated in the whole Dallas–Fort Worth area. Figure 18 shows a ratio of 23 in the middle of the rush period, but on average the ratio is around 28. This clearly shows that simulations like the one described here have enough computational speed for thorough investigations of large scale traffic problems.

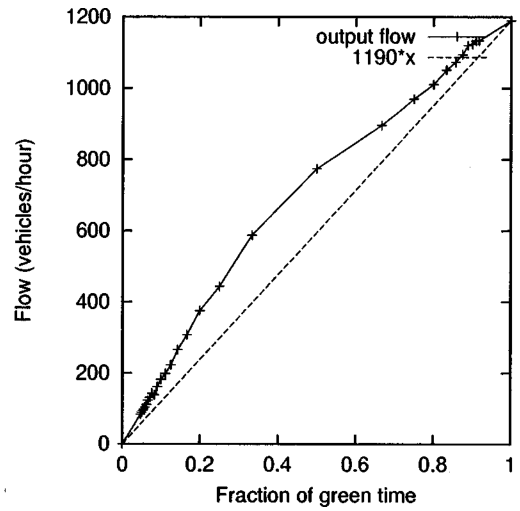

FIG. 14. Flow vs f_{green}.

IV. DISCUSSION

In the Introduction we argued that, because of congestion, tools with a better representation of the *dynamics* of transportation systems are needed. This requirement can, at least in principle, be fulfilled by a microscopic approach, microscopic meaning here that each vehicle and each traveler are individually resolved. Because of the complicatedness of the real world, analytical approaches here seem hopeless so one resorts to simulation.

On the other hand, we have also argued that, again because of congestion, one needs to consider much larger temporal and spatial scales than ever before. This, together with the requirement of a microscopic resolution, leads to a considerable computational challenge. In order to meet this challenge, one possibility is to use simplified models for the transportation system dynamics that still have a microscopic resolution. Yet, these simplifications come at a price because some aspects of reality will be represented with a reduced fidelity. It is an important research problem to understand the *consequences* of these simplifications. Note, though, that this question needs to be answered on the level of the transportation planning questions that our model is meant for, and it is far from clear how certain microscopic simplifications affect that macroscopic behavior that is important for those questions.

As a result, it seems necessary to us to attempt to understand the advantages and problems of several different simplified microscopic models from both the microscopic and macroscopic perspectives. As discussed in the Introduction, the model presented in this paper falls into a class of models that use ''simplified link dynamics'' [9–12]. In the most extreme case, vehicles are moved directly to the end of the link where they wait in a queue until they can leave the link. The waiting conditions in the queue can be, for example, time constraints (vehicle needs a certain amount of time to traverse the link), capacity constraints (vehicles can only leave at certain rate), and space constraints at destination links (destination links may be full). Note that, in a more realistic microsimulation, all these numbers would be *generated* by the simulated dynamics instead of being included as calibration parameters. Also note that some aspects of the dynamics irrevocably get lost in the simplified models even

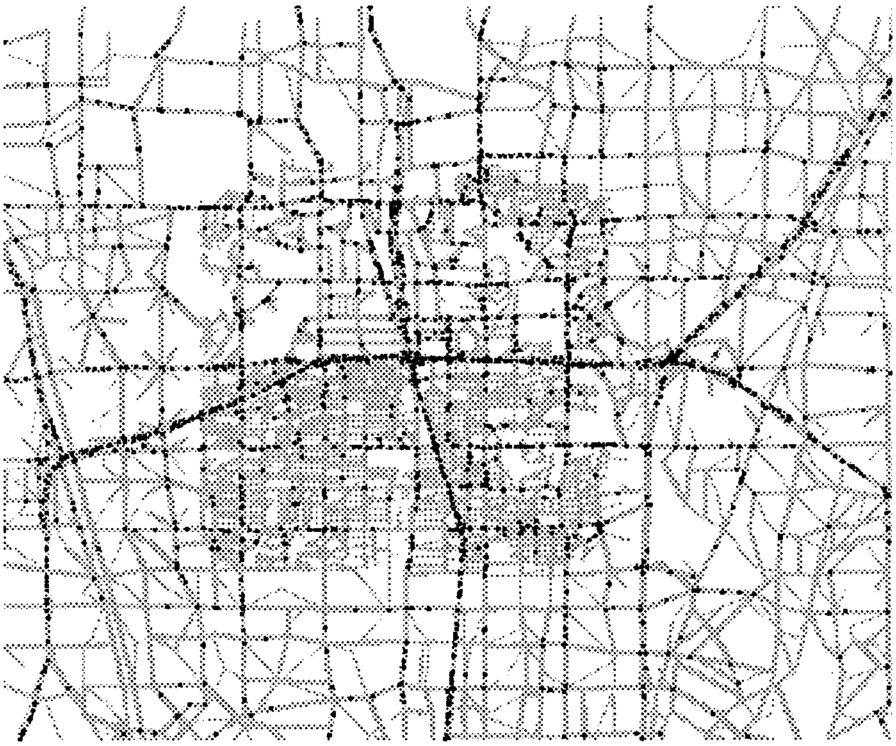

FIG. 15. Snapshot of the case study area at 7:00 am.

with the best of all possible calibrations. Examples of this are the effects of signal phasing, of turn pockets, or of lane changing. All of these are certainly important on a more microscopic problem scale (such as traffic ''operations''), but it is unclear how important they are on the scale of transportation planning. And also remember that using a highly realistic model sometimes is not an option, for example, because of computational restrictions or data collection restrictions. In such cases, knowing the different limitations of different simplified models becomes crucial in order to select the best one for a given question, or decide that the question cannot be answered with the available technology.

The model in this paper also uses capacity constraints at the end of the link (these are the p_{trans} or f_{green} parameters), but it attempts to capture some of the link dynamics, such as speed limits, limited ''storing'' capacity on jammed links, or backtraveling ''holes'' in jammed situations, directly. For this, it uses a one-lane representation of the traffic dynamics, which is somewhere between a simple queue representation and a realistic multilane implementation. Since a one-lane representation cannot carry the full throughput of a multilane road, this implies a subsampling of the population, i.e., only a certain fraction of all travelers is used in the simulation.

We have stressed several times in this paper that microscopic evaluations of different models are not enough; they need to be evaluated in the context of transportation planning questions. For the current model, such evaluations are under way, but are beyond the scope of this paper. A paper that compares the performance of the microsimulation presented in this paper with two other microsimulations and with field measurements in Dallas (Texas) is close to completion [27]; further work using data from Portland (Oregon) is in preparation.

V. SUMMARY

''Blockage'' sites, i.e., sites that move particles or vehicles only a fraction of the time, reduce the maximum throughput of a link of cellular automata models for traffic flow and particle movement studies. We have systematically tested the effects of three different blockage schemes, where one was the usual random draw, one was a regular traffic light with long red and green times, and one was what we called a ''Dirac'' traffic light because it had 1-sec spikes of one color. In general, there is no linear relation between the

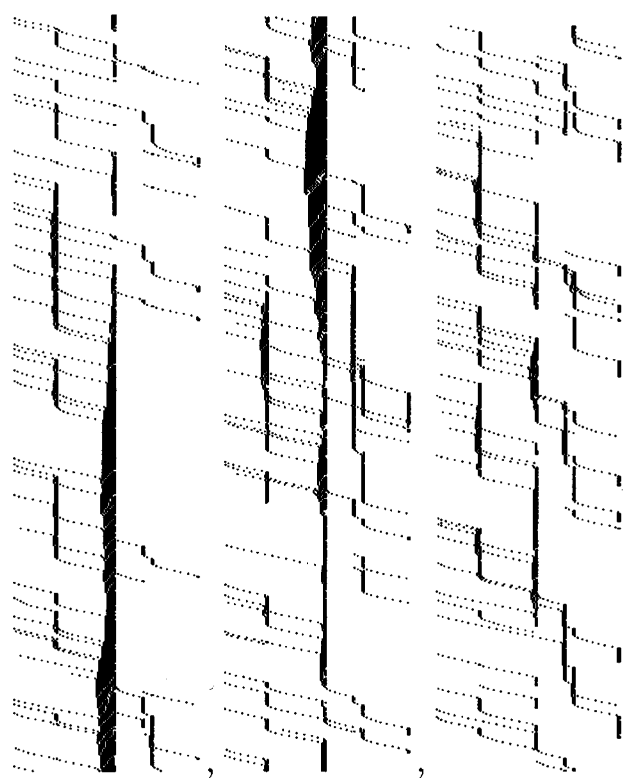

FIG. 16. Space-time plot of a particular link (Beltline Rd., an east-west arterial in the northern part of the area) from 7:00 to 7:05 am (left), 7:30 to 7:35 am (middle), and 8:00 to 8:05 am (right).

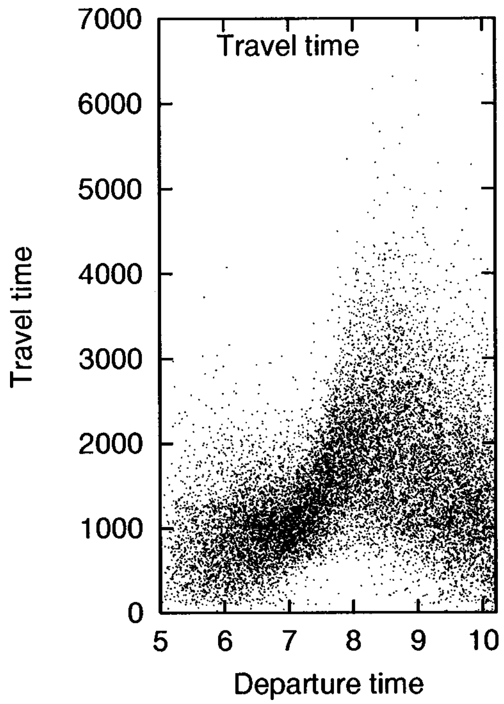

FIG. 17. Travel times vs departure time.

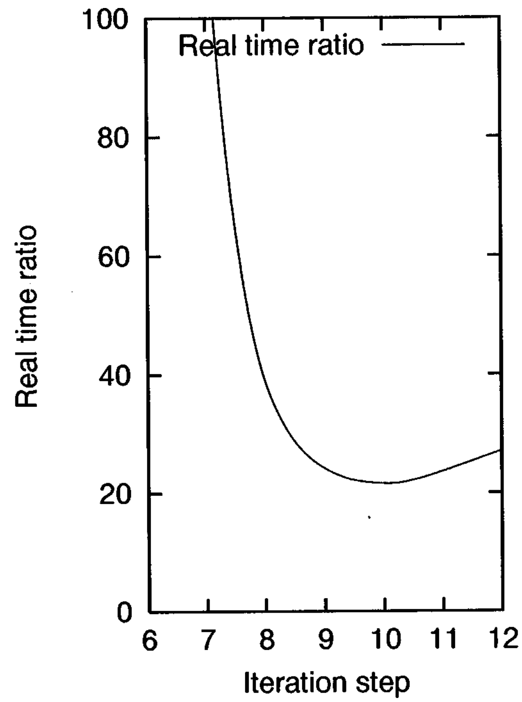

FIG. 18. Real time ratio.

fraction of green time and the throughput. The Dirac traffic light returned the highest throughput; the explanation for this is the ''particle-hole'' attraction that can be found in the type of cellular automaton that was used. Since none of the timing schemes returns a totally linear relation, we used the random scheme in an implementation of traffic in Dallas. We showed some exemplary results of this implementation.

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[18] This paper will concentrate on the flow variable alone, making the following somewhat less important. The argument for the scaling of the CA is as follows [17]: If every site in the CA is occupied, this should correspond to the jam density, leading to a cell size of approx. 7.5 m. Fundamental diagrams (i.e., plot-

ting flow versus density) should display maximum flow at densities between 15 and 30 veh/km (depending on the country and on the vehicle fleet mix); this is obtained by using a maximum velocity v_{max} of 4 or 5 cells/iteration in the CA. 5 cells/iteration should then correspond to fairly fast vehicles, say 135 km/h. This leads to a time step of one second.

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