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Parallel Computing 27 (2001) 719–735

PARALLEL COMPUTING

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A cellular automaton traffic flow model for online simulation of traffic

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Received 31 March 1999; received in revised form 20 December 1999

Abstract

Spatially and temporally dissolved information about traffic states in road networks is a basic requirement for the application of intelligent transport systems (ITS). We present a concept for online simulations of traffic in road networks: real-time traffic data stemming from inductive loops serve as input for high-speed microsimulations using a cellular automaton traffic flow model. The quality of the reproduced traffic states is investigated with regard to vehicular densities and link travel times. As an example for dynamic traffic management we studied different strategies for individual en-route guidance systems and their efficiencies. For all investigations the road network of Duisburg served as the study area. © 2001 Elsevier Science B.V. All rights reserved.

Keywords: Online simulation; Cellular automata; Traffic flow; Intelligent transportation systems (ITS)

1. Introduction

In modern societies the demand for mobility is increasing daily and the capacities of the road networks are saturated or even exceeded. Especially, in densely populated regions it is socially untenable to expand the networks further to relax the situation. Thus, the existing infrastructures have to be used more efficiently. Meanwhile, a lot of work has been done to develop intelligent transport systems (e.g., [1,2]), like dynamic route guidance systems which offer optimal travel routes.

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To propose such routes these systems need evaluation criteria and a good knowledge base of the *current* traffic state.

Typically, traffic data are collected by locally fixed detectors like inductive loops or cameras. In most areas these are installed at the surroundings of crossings in order to control and optimise the traffic signals at a single node. However, in many cities the road network is not adequately equipped with detection devices to gather information about the current traffic state in the whole network at once.

A feasible way to derive traffic loads for those regions not covered by measurements is to combine local traffic counts with a suitable traffic flow model under consideration of the infrastructure (i.e., type of roads, priority regulations at the nodes, etc.). This is the basic idea of online simulations: *Local traffic counts serve as input for traffic flow simulations to provide network-wide information*. This approach is advantageous since all static entities of the network like its structure or the traffic light management are incorporated directly in the simulation dynamics.

The outline of this paper is as follows. In Section 2 the cellular automaton approach for the simulation is introduced. The underlying road network and the used database are described in Section 3. Within this section some technical remarks about the construction of the road network are given. Some measurements in the network and the reproduction of traffic states are discussed in Sections 4 and 5. A route guidance system is described in Section 6. In Section 8 it is shown how the simulation tool can be extended to describe freeway networks.

2. The cellular automaton model

As pointed out in Section 1 the prediction and modelling of traffic flow is one of the future challenges to sciences [2–5] and is of interest for both applications as well as theoretical investigations.

In principle, there are two different approaches towards the problem. On the one hand traffic flow can be characterised by macroscopic entities like mean velocity, global density or flux (macroscopic approach, e.g., [8,9]). On the other hand the motion of single vehicles can be resolved (microscopic approach, e.g., [7,10–13]).

In general, traffic flow models should describe the relevant aspects of the flow dynamics as simply as possible by keeping track of the essentials. In this spirit one tries to model the individual driving behaviour, i.e., follow the microscopic approach, like car-following models [10,11], where the behaviour of a driver depends only on its predecessor. Nevertheless, the numerical effort of such detailed models is very high and it is hardly possible to apply them to realistic networks. Since cellular automata are by design ideal for large-scale computer simulations [14] they can be efficiently used to describe traffic flow.

In 1992 Nagel and Schreckenberg [7] introduced a very simple cellular automaton model which provides a microscopic description of the vehicular motion using a set of update rules. Although it is one of the simplest traffic flow models, it is nevertheless capable of reproducing important properties of real traffic flow, like the density-flow relation and the spatio-temporal evolution of jams [6] (Fig. 1).

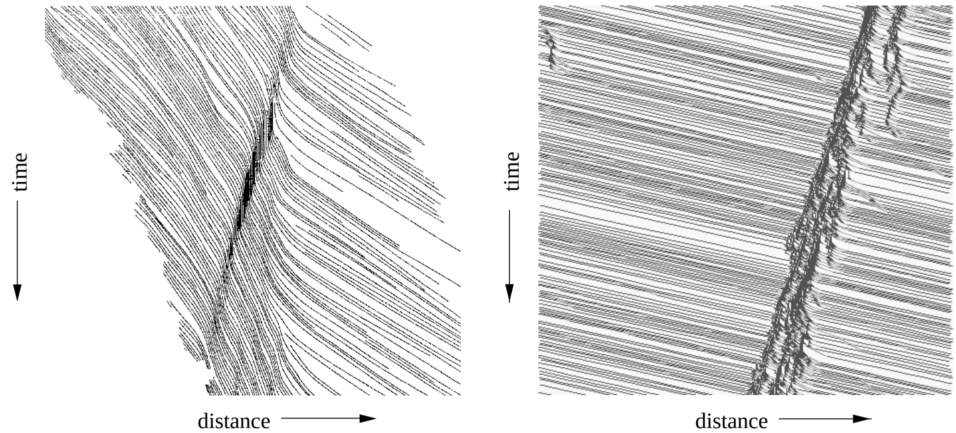

Fig. 1. Time vs. space plot of density waves. Each trajectory represents a vehicle. The left picture was generated by using video sequences taken from an American freeway [6] and shows the spontaneous emerging of a jam. Similar structures can be obtained by simulations using the Nagel–Schreckenberg model [7] (right picture, $v_{\max} = 5$, $p = 0.5$).

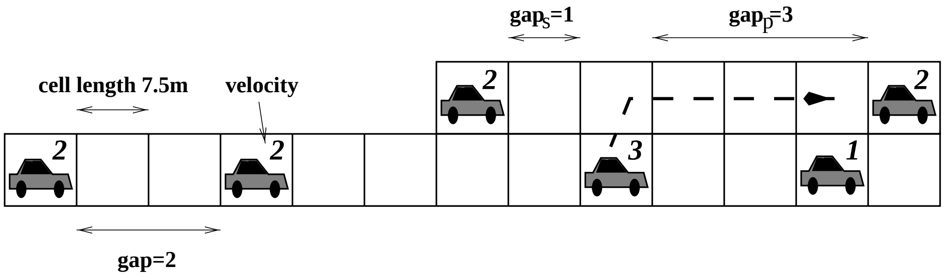

Fig. 2. Part of a road in the Nagel–Schreckenberg model. It is subdivided into cells, which are 7.5 m long. Each car has a discrete velocity $v \in \{0, \ldots, v_{\max}\}$. Its velocity is restricted by the headway gap. For a safe lane change two more gaps on the alternative lane gap$_s$, gap$_p$ have to be taken into account.

For completeness, we recall the definition of the Nagel–Schreckenberg model for single-lane traffic. The road is subdivided into cells with a length of $\Delta x = \rho_{\text{jam}}^{-1} = 7.5$ m, with $\rho_{\text{jam}} \approx 133$ veh/km the density of jammed cars (Fig. 2). Each cell i is either empty or occupied by only one vehicle with a discrete speed $v_i \in \{0, \ldots, v_{\max}\}$, with $v_{\max}$ the maximum speed. The motion of the vehicles is described by the following rules (*parallel dynamics*):

1. Acceleration: $v_i \leftarrow \min(v_i + 1, v_{\max})$.
2. Deceleration to avoid accidents: $v_i' \leftarrow \min(v_i, \text{gap})$.
3. Randomisation: with a certain probability p do $v_i'' \leftarrow \max(v_i' - 1, 0)$.
4. Movement: $x_i \leftarrow x_i + v_i''$.

The variable gap$_i$ is the number of empty cells in front of the vehicle at cell i. A time step corresponds to $\Delta t \approx 1$ s, the typical reaction time of a driver. With a maximum speed $v_{\max} = 5$ cells/time-step the cars can speed up to 135 km/h. Note that

$v_{\max}$ reflects the speed desired by the majority of drivers if they would not be hindered by other vehicles and there is no limit due to technical reasons. In reality, the "desired" speed spreads widely. Note also that a single vehicle might exhibit unrealistic behaviour from a microscopic point of view like slowing down from maximum speed to zero within one time step.

What is the interpretation of the update rules? The first two rules describe a somehow optimal driving strategy, the driver accelerates if the vehicle has not reached the maximum speed $v_{\max}$ and brakes to avoid accidents, which are explicitly excluded. This can be summed up as follows: *drive as fast as you can and stop if you have to!* Such a cellular automaton is deterministic and the stationary state depends only on the initial conditions.

But drivers do not react in this optimal sense. They vary their driving behaviour without any obvious reasons. Therefore it is necessary to introduce the so-called *braking noise p* (rule 3) which is essential for a realistic description of traffic flow. It mimics the complex interactions between the vehicles and is also responsible for the spontaneous formation of jams. A comparison with experimental results [6] shows that the macroscopic features of traffic flow are reproduced quite well (Fig. 1). An analytical description of the model is hardly possible, although it can be solved in certain limits, e.g., $v_{\max} = 1$ or $p \to 0$ ([15] and references therein).

The fundamental relations reflect the dependencies between the density ρ, the velocity v and the flow Φ, which (from a global point of view) are given by

$$\rho = \frac{N}{L}, \quad \langle v \rangle = \sum_{i=j}^{N} v_j, \quad \Phi = \rho \langle v \rangle. \tag{1}$$

This is valid for a system with N vehicles and L cells. In Fig. 3 the global fundamental diagram for different values of $v_{\max}$ and braking noise p is shown. The

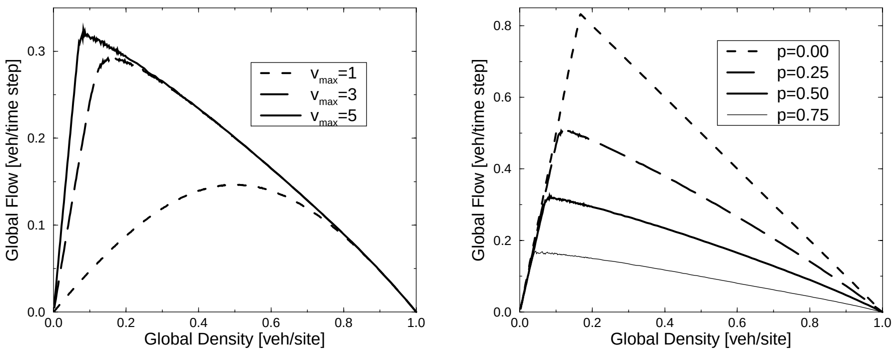

Fig. 3. Density-flow (fundamental) diagrams of the Nagel–Schreckenberg model with different parameters. The measurements were averaged over 5000 time steps in a system of $L = 5000$ sites. In the left diagram the maximum speed $v_{\max}$ is varied with $p = 0.5$. Note for $v_{\max} = 1$ the flow-density relationship is symmetric due to the underlying particle-hole symmetry. The right diagram shows the fundamental relation (1) for different deceleration probabilities p with $v_{\max} = 5$. The higher p the lower is the maximum flow in the system.

simulations were performed in a system $L = 5000$. With increasing $v_{\max}$ the dynamics change drastically. Especially, the particle-hole symmetry is broken for systems with $v_{\max} > 1$. Increasing the braking noise leads to higher fluctuations resulting in a collapse in the flow at lower densities.

In fact, more detailed measurements of highway traffic [16–19] yield that the flow is not a unique function of density, like in relation (1) suggested. In some the density regimes two branches in the fundamental diagram coexist. The upper branch of higher flow can be characterised by negligible interactions between vehicles, jams do not emerge. A system in the lower branch shows homogeneous flow as well as large jams with phase separation. The high-flow states are called *meta-stable* and have not been observed in simulations with the original Nagel–Schreckenberg model. But with a velocity-dependent randomisation (VDR) Barlovic et al. [13] generated meta-stable states. In a VDR model the deceleration probabilities are velocity dependent, i.e., $p = p(v)$. A continuous extension of the cellular automaton which also shows meta-stable states was proposed by Krauß et al. [12,20].

Another phenomenon observed in real traffic at intermediate densities is the *synchronised flow* [17,19]. If a transition from free flow to congested flow takes place it sometimes yields a sudden drop in speed but the flow remains nearly constant. The new phase in the jammed region is called synchronised flow. But its nature as well as its reasons are still under discussion.

Nevertheless, it has been shown that the Nagel–Schreckenberg model is sufficient to model traffic flow in urban networks. In order to describe multi-lane traffic the set of fundamental rules has to be expanded. This extension has to be carried out with regard to security aspects and legal constraints, which vary from country with the considered country (e.g., [21] and references therein).

For completeness, we only sketch the idea of a lane change. In Fig. 2 a part of a two-lane road is depicted. First, the vehicle on cell i checks if it is hindered by the predecessor on its own lane. This is fulfilled for $\text{gap}_i < v_i$. For a lane change it has to take into account the gap to the successor gap_s and to the predecessor gap_p on the alternative lane. If the gaps allow a safe change it moves to the other lane. A systematic approach for two-lane traffic can be found in [21].

3. Road network and traffic data

Although an urban road network is very complex, it has been shown [22] that arbitrary kinds of roads and intersections can be constructed with only a few basic elements. With these elements it is possible to design the complete road network of a city like Duisburg, an area of about 30 km^2 (Fig. 4). In the following an edge corresponds to a driving direction on a road, i.e., each road usually consists of two edges. For each road the number of lanes, the turning pockets, the traffic light management and the detailed priority rules are included into the simulation. The network consists of 107 nodes (61 signalised, 22 unsignalised and 24 boundary nodes), 280 edges and 22.059 cells corresponding to about 165 km. The boundary nodes are the sources or sinks of the network, respectively.

Fig. 4. Sketch of the simulated road network with check points (filled circles) and sources and drains (letters). At the check points the data of all lanes of the road are accessible.

For an *online* simulation the model has to be supplemented by traffic data gathered from detection units distributed all over the city. Every minute the measurements of about 750 inductive loops (approx. 4 kBytes) are sent from the traffic computer of the municipal authority of Duisburg to the online simulation computer (Fig. 5). These data are used to calculate the turning probabilities and to tune the simulation which will be explained later on.

There are different strategies to run a microsimulation in such a network. On the one hand one can use origin-destination matrices, i.e., information about the trips people want to take in the network. Since such data with sufficient temporal and spatial resolution are hardly available, vehicles are driven randomly through the network. This means that the cars do not follow a predefined route. Instead, they choose their way at every node according to a turning probability. These turning probabilities have to computed by real traffic data. Currently, turn counts can be derived directly for 56 driving directions. In addition, the turning probabilities were

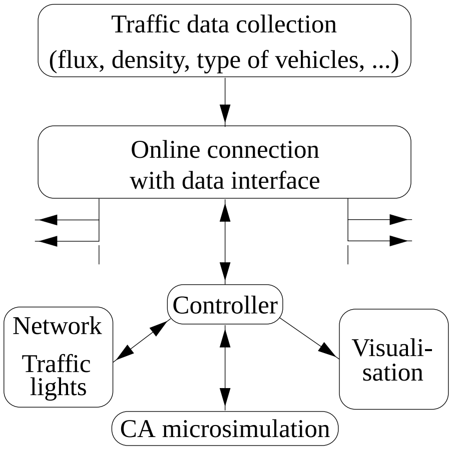

Fig. 5. Flowchart of OLSIM. The traffic data are sent via an online connection to the Controller. The Controller handles static information like the network structure and performs CA microsimulations. The results can be visualised and processed by intelligent transport systems.

completed by manual counts in order to get at least the average number of turning vehicles at crossings which are not covered by measurements.

The collected data are also used to tune the microsimulation. At the so-called *results* the traffic data calculated by the simulation and the real measurements are compared (Fig. 6) and differences are determined. According to these differences the number of passing vehicles is changed by adding or removing vehicles. The check points serve as internal sources and sinks. It is convenient to perform these adjustments, because at such a point (altogether there are 51 of them) all lanes of the road are equipped with detection units and a complete cross-section is available (Fig. 6).

There are two feasible ways of tuning, either by adapting densities or flows. But the same flow, is connected with two different densities, as it can be seen in the fundamental diagram (Fig. 3). Therefore, flow-tuning may cause problems. The flow can be easily expressed by the number of cars N_p passing a check point during a simulation interval $\Delta\tau$:

$$\Phi_\mathrm{l} = \frac{N_\mathrm{p}}{\Delta\tau}. \tag{2}$$

There are two ways to estimate the local density: (a) by summing up the times t_k^occu vehicles are covering the area of an inductive loop or (b) according to relation (1), if the speeds v_k are accessible. This is done with respect to the number of time steps N_s during which vehicles are stopping directly above an inductive loop (only available in simulations):

$$\text{(a)} \quad \rho_\mathrm{l} = \frac{1}{\Delta\tau}\sum_{k=0}^{N_\mathrm{p}} t_k^\mathrm{occu}, \quad \text{(b)} \quad \rho_\mathrm{l} = \frac{N_\mathrm{p}^2}{\Delta\tau\sum_k v_k} + \frac{N_\mathrm{s}}{\Delta\tau}. \tag{3}$$

Fig. 6. Sketch of the simulated road network with check points (compare Fig. 4). At the check points the local flow can be tuned with respect to the empirical data collected. The digits denote the mean change rates (cars per minute, averaged over 24 h) of passing vehicles.

The most convenient method, which has been applied here, is the calculation of the density on a complete edge or at least of a part of it: if n vehicles are occupying a link of length z_e, the edge is defined by

$$\text{(c)}\ \rho_1 = \frac{n}{z_e}. \tag{4}$$

Our simulations showed that both methods, namely tuning the flow or the density, respectively, lead to the same results. Special check points are the boundary nodes – here the empirical traffic data directly generate the rates of vehicles flowing in and out. Unfortunately, the network is quite small so that there are many boundary nodes which influence the results strongly.

In Fig. 6 the differences between measurement and simulation in units of vehicles per time interval (typically 1 min) are shown. Obviously, at the majority of check points vehicles have to be added, i.e., there are additional sources in the network like smaller streets or parking lots, which are not recorded by the detection units. This is one main difference between urban and freeways traffic. On freeways sources and sinks are well defined by on- and off-ramps, and it is easy to handle them and to collect the data. Thus, reliable results for the online simulation can only be obtained in the centre of Duisburg, where the density of check points is sufficiently high.

4. Results of the network simulation

The online simulation enables one to interpolate the traffic state between different check points (which are typically close to intersections). But it is also possible to gather information about those areas not well equipped with detection units. The current traffic state of the whole city of Duisburg is calculated and published every minute in the Internet [23] (Fig. 7). The results can also serve as the starting point for planning a trip. Additionally, there are other pre-trip information available like the current and future roadworks in the city of Duisburg.

The empirical and numerical results allow more detailed examinations of network traffic (Fig. 8). In general, the number of simulated cars is higher than the number of detected cars – a result of the extrapolation. Since every road user has certain habits nearly every weekday has its own peculiarities, like rush-hours. On a typical Wednesday (left column in Fig. 8) the commuters cause a sharp peak in the morning rush-hour. Due to shopping traffic, flexible working times and people working overtime the afternoon-peak is broadened but it is still higher than in the morning. Smaller peaks in the early morning or in the late evening are caused by shift-workers.

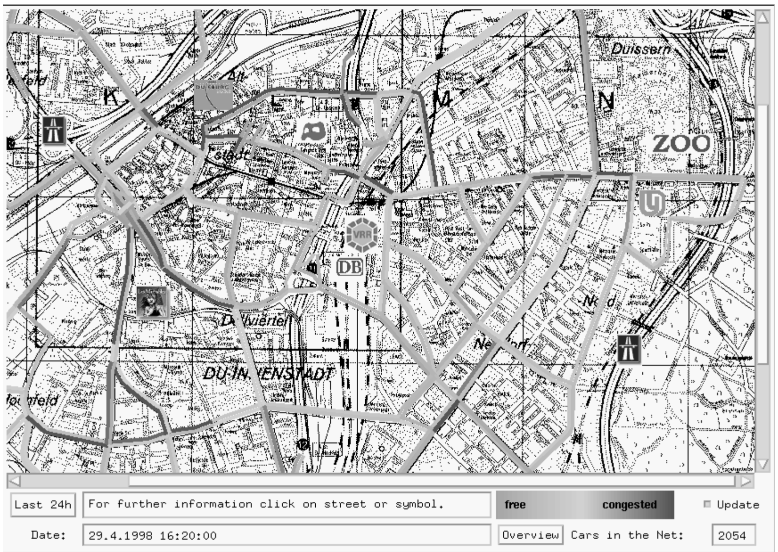

Fig. 7. Screen shot of the interactive map published every minute in the Internet [23]. The roads are coloured according to the traffic loads calculated during the previous minute.

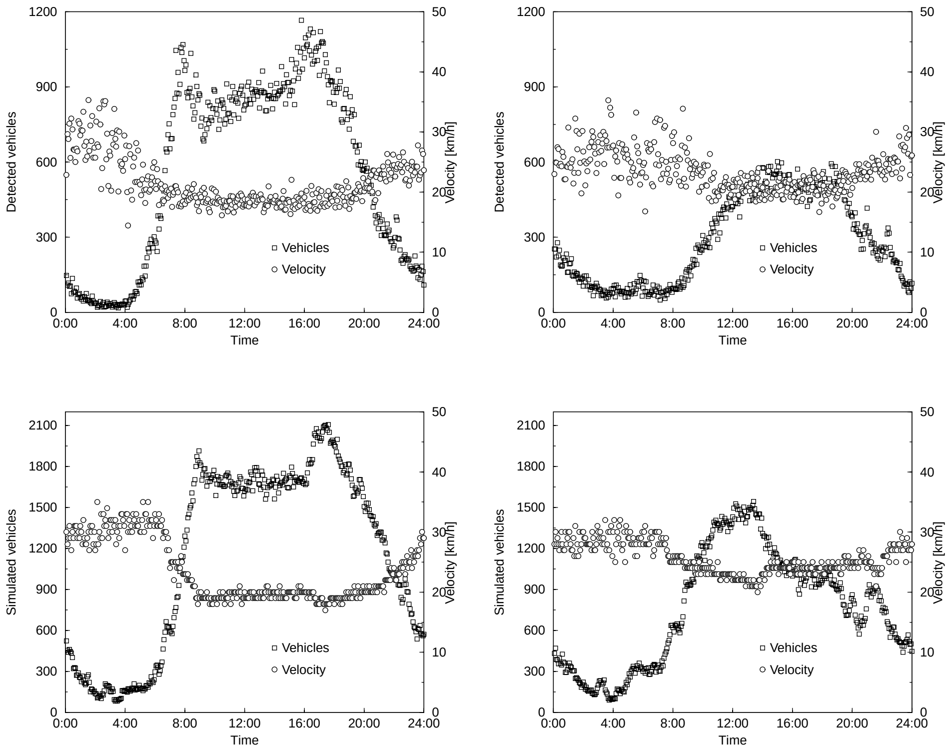

Fig. 8. Comparison between the empirical (upper row) and simulation results (lower row) as well as a typical Wednesday (left column) and a typical Sunday (right column). In every plot the number of detected (simulated) cars and the mean velocity is shown during a day. Since Wednesday is a working day, the typical characteristics like morning and evening rush-hours can be found. The difference between detected cars and simulated cars can be explained as follows: The number of detected cars is an accumulation of all measured cars. The simulated cars are all cars which are in the network. So the difference between the two numbers are the cars which have not reached a check point during the last minute. The characteristic of a Sunday differs strongly from the typical weekday. At night the mean velocity is higher than at day, but its variance increases due to the more significant contribution of both the standing cars at intersection and moving cars with high speed on the links.

These peaks can also be detected on Sunday (right column in Fig. 8). Additionally, the background traffic on Saturday night is also risen (“Saturday Night Fever”).

In general, the lower number of vehicles driving at night leads to an increased variance of the measured or simulated speed, respectively. Stopping cars at crossings heavily affect the statistics. However, it is likely to find drivers who drive very fast since the roads are quite empty. During the day all these fluctuations are smoothed out. The network is dominated by the intersections and their priority rules or traffic lights. On the roads between intersections the behaviour of drivers is constrained by platoon forming – nearly everyone behaves in a similar way irrespective of their individual preferences or the engine performance.

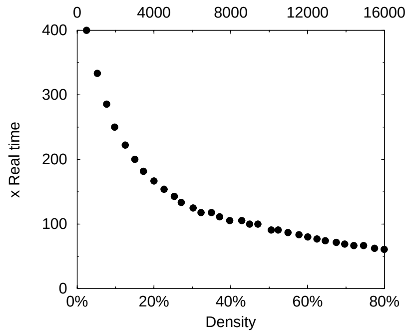

Fig. 9. Simulation speed vs. density. The simulations were performed on a Pentium 133 MHz. The speed depends on the reciproce number of simulated cars. For the most likely density interval the road network of Duisburg can be simulated approximately 100 times faster than real time.

The effect of smoothing out fluctuations cannot only be observed between day and night, but also between empirical and simulated results. For the empirical data the drivers' behaviour at the intersection mainly contributes to the statistics, whereas in the simulation travelling cars on the link have greater impact. This is also responsible for the slightly increased mean velocity.

A basic condition for performing online simulations or *traffic forecast* is a simulation speed higher than real time even for large networks. It has been shown using the cellular automaton approach that simulations of the whole highway network of Germany can be performed faster than real time on a parallel computer [24]. As depicted in Fig. 9, the simulation of a network of the order of magnitude of Duisburg can be easily performed on a common personal computer (Pentium 133 MHz). The simulation includes the data transfer between the diverse components of the application as well as the handling of the traffic lights. Within the interesting density interval (10–40%, ≈2000–8000 vehicles in the network) it takes less than one second to perform a simulation of 1 min in real time. The remaining time may be used to calculate several routes (see Section 6) to simulate several scenarios under varying conditions or to estimate the traffic state expected within the next few minutes.

5. Reproducing traffic states

A sensitive test for the quality of the online simulation is the ability to reproduce given traffic states. Because network-wide information cannot be obtained from the online measurements, we have to compare the results of the online simulations with artificial states (*reference states*) generated by an independent simulation run. In other words, we perform two simulation runs with two independent sets of random numbers, but the same set of simulation parameters (e.g., source rates). After reaching the stationary state, we estimate the reproduction rate of the local density according to the following quantity:

$$R_\rho = \frac{1}{Z}\sum_{e=1}^{N_e} z_e(1 - |\rho_e - \bar{\rho}_e|) \quad \text{with } Z = \sum_{e=1}^{N_e} z_e. \tag{5}$$

The edges are weighted by z_e the number of cells on the edge (hence Z denotes the total number of all cells of all N_e edges). The local density of an edge in the second run ρ_e is compared with the local density of the same edge $\bar{\rho}_e$ drawn from the reference state. Each measurement point serves as possible check point in the reference run.

In Fig. 10 the reproduction rate is shown dependent on the probability p_{mp} that a measure point is actually used as check point. The results are given for two different values of the input rates at the boundary nodes (scenarios 1 and 2). For obvious reasons, the similarity of the states increases for higher p_{mp}. But for small values of p_{mp} the reproduction rate does not increase monotonously. This is due to the fact that the reproduction rate strongly depends on the position of the check points in the network. In order to show this effect we used a completely new check point configuration for each value of p_{mp}. It should be mentioned that even for the empty network (without any check points) high reproduction rates can be obtained, if the input rates of the simulation and the reference state are the same. Therefore, it should be possible to extrapolate future states of the network with a reasonable accuracy using online simulations.

Comparing both scenarios we can see that the reproduction rate is higher for smaller input rates. This means that it is more difficult to reproduce high density states. Finally, we consider two special cases which are depicted in Fig. 10 as dashed and dotted lines. R_ρ^{ran} denotes the reproduction rate we obtain if the simulation and reproduction only differ by the set of used random numbers, i.e., the measurements are starting with two identical system copies. For large value of p_{mp} a higher reproduction rate than R_ρ^{ran} can be achieved, because the check points also store the fluctuations in the reference run leading to an extremely high value of R_ρ. The re-

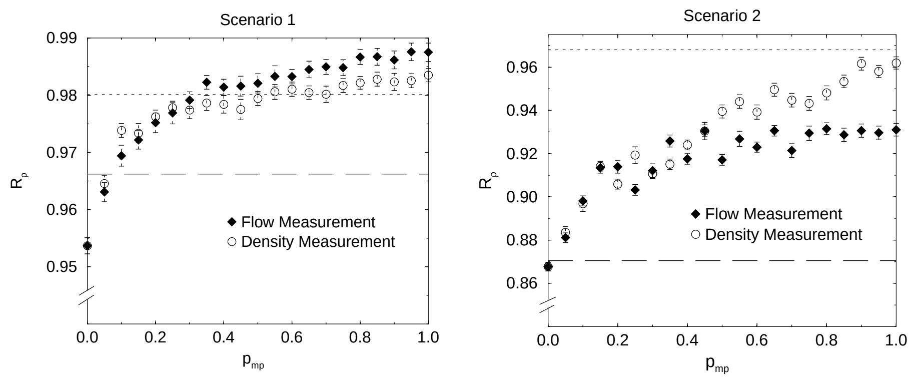

Fig. 10. Similarity $R_\rho(p_{\mathrm{mp}})$ resulting from reproducing traffic states of two scenarios. Simulations in scenario 1 (2) are performed with an input rate $r_s = 0.1$ (0.5) at the boundary nodes. Additionally, the special reproduction rates R_ρ^{ran} (dotted line) and R_ρ^{h} (dashed line) are shown.

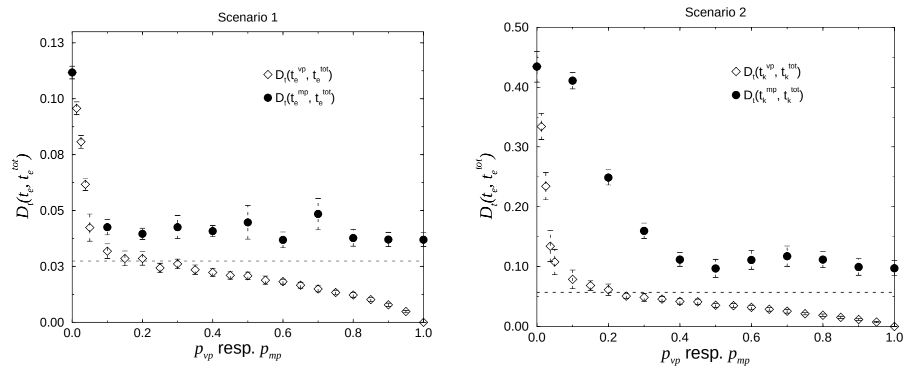

Fig. 11. Travel time differences according to (6). The similarity of the compared states increases with the density of floating cars (FC), respectively, measurement points (MP). The dotted line represents a reference run which only differs in the set of random numbers used, data below this line characterise a usable reproduction rates.

production rate R_ρ^{h} denotes the results obtained for an initial homogeneous state in the reference run.

Another criterion for the evaluation of the quality of the reproduced traffic state is the link travel time between two intersections. We define a parameter D_t which corresponds to the difference of travel times measured in two different simulation runs:

$$D_t(t_k, \bar{t}_k) = \frac{1}{T} \sum_k |t_k - \bar{t}_k| \quad \text{with } T = \sum_k \bar{t}_k. \tag{6}$$

The results are shown in Fig. 11 for two different configurations. The measurements enclose data collections by floating cars (FC) which leads to a more satisfying approach to the reference state. FC are moving with the traffic flow and work like a measure probe.

6. Dynamic route guidance

In Sections 1–5 we have seen that the online simulation estimates the actual traffic densities and the average velocities on the links. This information can be processed in dynamic route guidance systems. In contrast to *static* route guidance systems which only incorporate static network data like infrastructure, *dynamic* route guidance systems use the actual traffic state. As a first application we investigated different routing strategies in the road network of Duisburg. Note that a certain rate of vehicles are therefore equipped with appropriate information like origin and destination of the trip. This means that they do not turn randomly at intersections like non-equipped vehicles.

Instead of calculating the routes for every demanding vehicle individually, the optimum routes are stored globally, so that the same route recommendations are

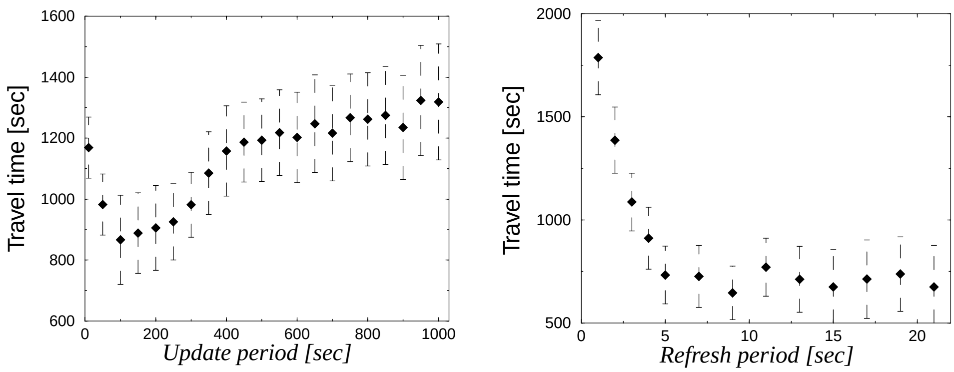

Fig. 12. Overall travel time vs. update and refresh period. It is important to tune thoroughly the update period (left) and the refresh period (right) in order to get a better benefit for the drivers who rely on a dynamic route guidance system. The update period is the duration between two updates of the proposed route. For urban areas the travel time is minimised for an update period of $\approx$10 min. The refresh period is more artificial. It refers to the duration a stored time is taken into account for estimating link travel times. After the refresh period it will be replaced by a mean value. This has been done in order to cut off the temporal correlations of different traffic states.

given to all vehicles with the same trip information in every time step. After a predefined update interval the optimal routes are recalculated. For the edge costs we used both, link travel times (Fig. 12) as well as vehicle densities. While time-based routing yields shorter overall travel times, considering vehicle densities in the calculations allows to incorporate aspects like *driving comfort*. For this reason, both criteria have to be combined to provide route guidance systems, which go beyond the calculation of shortest paths with several weights. A very important parameter for commercial applications is the market penetration of the route guidance systems [25].

In the simple approach given above only one valuation criterion was chosen and optimised. To combine different criteria like route length, travel time and travel comfort, fuzzy systems can be implemented. In [26] *symmetric decision model* is used to allow multi-criteria optimisation. The link travel times are calculated by the online simulation and used as dynamical weights.

A route guidance tool based on this approach will be presented in the Internet [23]. The road user can choose a starting and destination point and a special trip is calculated. This can be optimised with regard to different criteria selected by the user. In addition to the dynamic routes further information like road works or timetables of other transportation modes can be accessed from an underlying GIS database. The effects of such a route guidance system on the network performance will be investigated in the near future.

7. Freeway traffic

An important share of traffic capacities is provided by freeways. Especially, for the online simulation of big cities it is necessary to incorporate them, since they are either an explicit part of the urban road network or at least their on- and off-ramps represent high-throughput sources and sinks. Duisburg, for example, is connected with three of the most frequented freeways in Germany, enclosing several highway intersections and numerous junctions.

In contrast to the simulation of urban traffic, freeway traffic is dominated by travelling on links between ramps or intersections. The typical length scale is of some 10 km, whereas in cities it is of some order of magnitudes smaller. Although Fig. 13 suggests that the system is somewhat different junctions and intersections are indeed simpler. Vehicles leaving or entering the freeway via on- and off-ramps can be treated like those which only want to change the lane. Only a few legal constraints have to be taken into account. Additionally, there are less turning decisions to make.

It has already been shown that even very large freeway networks (some 10 000 km with some millions of cars) can be simulated on high-performance parallel computers faster than real time [24]. So it is possible to carry out an online freeway traffic simulation [27]. Since the roads are well and homogeneously equipped with detection units (≈2500 measurement points in North-Rhine Westfalia covering complete cross-sections) the simulation can be supplemented by a proper set of data. The detectors are able to determine the speed of passing vehicles as well as to distinguish between vehicle type (passenger cars, trucks or trailers).

A further aspect and reason for performing freeway simulations is an extended and more useful application of route guidance systems. In urban areas alternative routes with a significant benefit are hardly to find. In freeway networks, especially in a quite dense one like the German Autobahn network, a lot of alternatives with much more benefit are found. This fact also causes the increased commercial interest

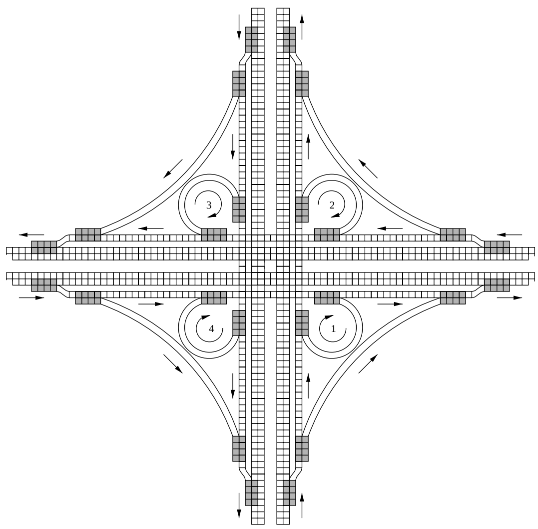

Fig. 13. A freeway intersection from the CA-point of view. Leaving or entering the freeway is similar to a lane change procedure which simplifies the handling in comparison to urban traffic simulations.

in collecting highway traffic data and generating useful information for potential costumers. Here, the simulation can serve as a tool for estimating travel times necessary to offer the best route available. Finally, the link between interstate traffic on highways and the local traffic in the cities can be achieved.

8. Summary

We presented a simulation tool for urban traffic which can be easily extended to model traffic flow on highways. The microscopic dynamics based on the Nagel–Schreckenberg cellular automaton permits the simulation of large-scale networks in multiple real-time. The network model encloses complex intersections and their priority rules as well as the handling of parking capacities and the circulations of public transports. We were able to show that the combination of a high-speed network simulation with traffic counts serves as a basis for further ITS applications. On the one hand by performing simulations we can extrapolate traffic states on a spatial and also a temporal scale, and on the other hand implement a useful laboratory environment for designing and evaluating dynamic traffic management system taking into account different criteria. Now, practical applications like an interactive and inter-modal support for planning a trip are conceivable.

Acknowledgements

The authors would like to thank K. Froese for digitising the Duisburg network and J. Lange, from the traffic control centre of the municipal authority of Duisburg, for providing the essential road network data and especially the online traffic data. We are also thankful to O. Annen, C. Gawron, S. Krauß, K. Nagel, M. Rickert, O. van Laak and P. Wagner for fruitful discussions and sharing insights. Parts of this work were developed within the framework of the North-Rhine Westfalia Research Cooperative *Traffic Simulation and Environmental Impact* NRW-FVU (Homepage: http://www.zpr.uni-koeln.de/Forschungsverbund-Verkehr-NRW).

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