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Traffic Forecast Using Simulations of Large Scale Networks

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Abstract— **In this contribution an approach to traffic forecast using a micro-simulator is presented. In order to provide network-wide information about the current traffic state a cellular automaton traffic flow model is combined with measured data. The framework is applied to the freeway network of North Rhine-Westphalia (NRW), where data from about 3,500 inductive loops are available and provided on-line minute by minute. Technical aspects of the simulation like the network structure are illustrated. Furthermore, heuristics are developed based on the statistical analysis of historical data.**

Keywords— **On-line Simulation, Cellular Automata, Forecast, Information Analysis, Real-time Systems, Traffic Data**

I. Introduction

MOBILITY is a vital good for the economic development of modern societies. Especially in densely populated regions, like the state of North Rhine-Westphalia, the capacity of the road network is not able to cope with the demand and it is social untenable to expand this infrastructure. Therefore, there is a seek for new traffic management and information systems to solve these problems.

One vital component of such systems is the prediction of traffic states. With regard to this, on-line simulations offer a powerful tool to reproduce traffic states of a large scale network virtually on one machine. Due to the increasing computational power, in recent years a lot of microscopic traffic simulators have been developed [1], [2], [3], [4]. Highspeed simulations performed faster than real-time are a basic requirement to forecast traffic states. To render the simulation as realistic as possible the simulation has to be coupled with real data. The growing number of inductive loops, infrared sensors, and video systems installed on the roads offers the opportunity to merge both: current and historical data with the simulation.

The remainder of the paper is structured as follows. In section II the principle of forecasting traffic states using on-line simulations is presented. The simulation model is introduced in section III. Special attention is paid to the network structure in section IV and the simulation technique in section V. In section VI an analysis of traffic data is carried out to incorporate historical data in the simulation for forecasts. In section VII first results of the simulation are presented and finally there is a summary and an outlook.

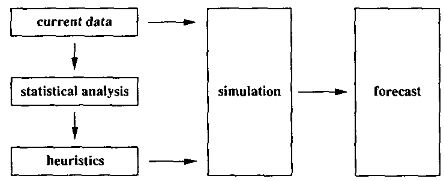

Fig. 1. Schematic sketch of the forecast procedure. The input to the simulator are current and historical data, which are provided in form of heuristics. Using both forecast is carried out.

II. How Do We Forecast?

There are many different ways for predicting traffic conditions. In general, the prognosis horizon is the first and most important parameter, since it determines, which procedure proves as the most effective forecast method. A second important detail is the input data, i.e., the number and the location of the sources of the data. Different approaches have been proposed in the past. Neural networks often are used for predicting traffic flow, speed data or travel times up to 15 minutes [5], [6]. To forecast traffic jams, spatial correlations can be used taking into account the dynamics of a moving jam [7], [8]. For a useful long-term prediction the current traffic data loose their weight and it is more important to use experience about the past, so-called heuristics, in form of a statistical data base consisting of traffic time series [9], [10], [11], [12].

Coupled with current and statistical data the use of on-line simulations supplies the possibility of both: short– and long–term forecasts of a whole network. To receive the current traffic state data are coupled directly with the simulation. To obtain a first prognosis the simulation has to be performed faster than real-time. Thereby, the main problem is to consider the traffic demand at the boundaries of the network in the simulation. Therefore, the collected data is analysed statistically to consider traffic states in form of heuristics that are useful for predictions. So, with regard to traffic forecasts the simulation tool serves as a connector of the current with the historical data (Fig. 1).

III. Simulation Model

A. Principle of On-line Simulation

The starting point for each traffic forecast should be information about the current traffic state in the whole network. Unfortunately, in most urban areas and freeway networks data are only available from separate points in the

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network. The common sources of information are inductive loops or video detection devices which provide data permanently. Other sources are event driven, like messages from the police or drivers with cellular phones. However, all information provided is local. Note that an exception to this rule are floating car data (FCD).

Our approach to provide network-wide information is to connect the local data with a micro-simulator. Thus, information can be derived for those regions which are not covered by measurements. The local traffic counts are combined with the network structure (i.e., type of roads, priority regulations at the nodes or on- and off-ramps) under consideration of realistic traffic flow dynamics. This is the basic idea of on-line simulations: *Local traffic counts serve as input for traffic flow simulations to provide network-wide information* [13].

B. Basic Model

Since the simulator is based on on-line data the model employed should be efficient. Due to their design cellular automaton models are very effective in large-scale network simulations [13], [14], [15], [16], [17], [18].

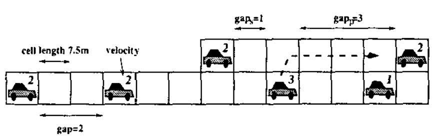

Fig. 2. Part of a road in a cellular automaton model.

Models which reproduce the dynamic phases of traffic are still under debate. Thus the original cellular automaton by Nagel and Schreckenberg [19] is used in a first version of this simulator. For completeness, the definition of the model is briefly reviewed. The road is subdivided in cells with a length of $\Delta x = \rho_{\text{jam}}^{-1} = 7.5$ m/veh, with the density of jammed cars $\rho_{\text{jam}} \approx 133$ veh/km (Fig. 2). Each cell is either empty or occupied by only one vehicle with an integer 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*):

R1 Acceleration: $v_i \leftarrow \min(v_i + 1, v_{\max})$,
R2 Deceleration to avoid accidents: $v_i' \leftarrow \min(v_i, gap)$,
R3 Randomization: with a certain probability p do $v_i'' \leftarrow \max(v_i' - 1, 0)$,
R4 Movement: $x_i \leftarrow x_i + v_i''$.

The variable *gap* denotes the number of empty cells in front of the vehicle at cell i. A time-step corresponds to $\Delta t \approx 1$ sec, the typical time a driver needs to react.

The first two rules (**R1, R2**) 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!* However, drivers do not react in this optimal way: they vary their driving behavior without any obvious reasons, reflected by the *braking noise* p (**R3**). It mimics the complex interactions between the vehicles and is also responsible for spontaneous formation of jams.

C. Lane Change

In order to describe more complex situations, e.g., multi-lane traffic or merging regions, the set of fundamental rules has to be expanded. For instance, a lane change has to be carried out with regard to safety aspects and legal constrains, which vary between different countries. A schematic lane change is shown in Fig. 2. First, a vehicle checks if it is hindered by the predecessor on its own lane. This is fulfilled if $gap < v$. Then 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 the vehicle moves to the other lane. A systematic approach for two-lane rules can be found in [20].

IV. Network Structure

A crucial point in the design of every simulator is the representation of the road network. In this section the design of the network is described. Like in other simulators the network consists of a few basic elements (e.g., [13], [21]). In the following, these basic elements are introduced. The data used for the network stems from the *NW*-SIB, a GIS system provided by the state of North Rhine-Westphalia.

A. Basic Elements

In principle, the whole network consists of two basic elements: links and nodes.

Nodes. A node is either a connection between two links or a sink/source at the boundary or an off/on-ramp. At the sources vehicles are added with regard to input data. On the sinks the cars are simply removed every time step.

Links. Links are directional elements that connect nodes. There are two kinds of links:

Multi-lane links. These links are the main parts of the network (Fig. 3). If they do not lead to a boundary node they are connected with another multi-lane link. The length of these links is often several kilometers. This is due to the way the network is constructed since at every on- and off-ramp and every intersection a node is set. Every multi-lane link has emission and absorption regions which are connected to the transfer links.

Transfer links. Compared to the multi-lane the transfer links are typically only a few hundred meters long and mostly single lane. They never lead directly to another edge. In fact, they have to be endowed with an acceleration region at the beginning and an emission region at the end, or a braking region at the beginning and an absorption region at the end.

B. Combined Elements

With the elements above one is able to build all freeway networks. Now, we will explain three combined elements:

- junctions,
- intersections, and
- triangular intersections.

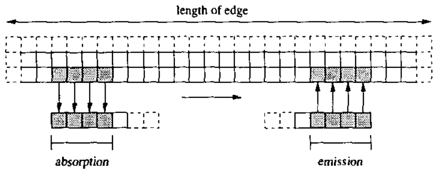

Fig. 3. A multi-lane link. Using an absorption or emission area, vehicles leave or enter a link. At the end of the link vehicles move on to the next with respect to their velocity.

Other geometries can rarely be found in reality. However, they can be constructed easily with the elements used here.

Junctions. Junctions generally consist of two on- and two off-ramps. Vehicles enter or leave the highway there.

Intersection. An intersection is a node in the network where two freeways meet (Fig. 4). Since they are very complex they comprise many transfer links. In order to leave a freeway and turn left or right to the other a vehicle has to use four different transfer links.

Triangular intersection. A triangular intersection is a node where two freeways meet, but one of them ends or begins, respectively.

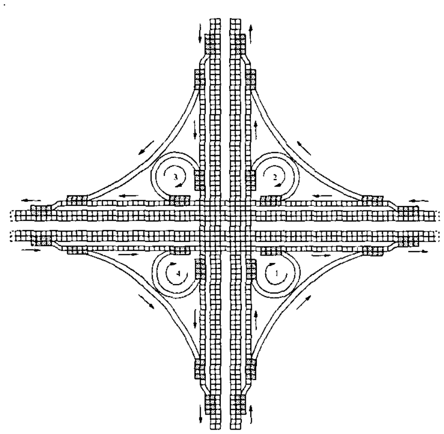

Fig. 4. Intersection in the network model. The two freeways are connected by transfer links, like parallel-lanes.

The basic elements described above have been used to construct the freeway network of North Rhine-Westphalia. It comprises 1,200 nodes, 3,560 links, 830 on- and off-ramps and 67 intersections. The overall length of the lanes is approximately 2,500 km, corresponding to 1,400,000 cells.

V. Simulation Technique

Up to now the basic concepts, i.e., the model and the network structure have been introduced. In the following, the guidance of the vehicles in the network and the algorithms used to incorporate the measured data into the simulation are described.

A. Guidance of the Vehicles

In principle, there are two different strategies to solve the route choice problem. One can assign an origin and a destination to the road user and they are guided through the network according to this route [14], [17]. For our network origin-destination information with a sufficient temporal and spatial resolution is not available. Therefore, the vehicles are guided in the network randomly, according to the tuning percentages calculated on the basis of the measured data.

B. Tuning Strategies

To incorporate the real world measurements into the simulation algorithms have to be found. This is done at the so-called checkpoints, which are located at those places in the network where a complete cross-section is available, i.e., all lanes are covered by an inductive loop. For realistic results it is crucial to incorporate the real world data in the simulation without perturbing the dynamics present in the network. Therefore, we propose a method which follows the idea to add the cars to the network "adiabatically", i.e., without disturbing the system. This method is therefore called "Tuning of the Mean Gap" [15].

The input to the tuning strategy is the difference between simulated and real world data. If the number of vehicles simulated is lower than the number measured, vehicles have to be added in an area around the check-point. In this area the mean gap $\langle g \rangle$ of the vehicles is calculated. From the real world data a speed v_{in} in cells/time step is determined. Now the cars are added to the system with regard to the mean gap $\langle g \rangle$ and their speed v_{in}.

Thus, the cars which are already on the track are not disturbed; in other words no car has to brake due to the added ones. If it is not possible to add the required number some vehicles are left out. Although this is not correct, it is more important to keep the dynamics of the system. It turns out that the strategy is capable of reproducing the traffic state quite well [15].

VI. Incorporation of Historical Data

The simulations describe the dynamics in a network but are lacking information about the boundaries. Especially for forecasts, reasonable data has to be incorporated. Therefore, heuristics will be used to predict the flow of the sources. In order to develop heuristics for traffic forecast, i.e., experience about recurrent events, historical data have to be analysed. Therefore, it is useful to classify certain days and events in categories [9], [12], [22], [23]. Two different characteristics can be distinguished: daily and seasonal. Seasonal differences arise, e.g., due to school holidays. On the other hand, there are daily differences: on working days a sharp morning peak is found which is absent on Sundays or holidays. Additionally, there are special unpredictable events. Due to the fact that for a sufficient statistical analysis not enough data are available from the freeway network yet, the following aspects are the results of a statistical analysis of 750 inductive loops of the urban network of Duisburg.

A. Daily Characteristics

In order to classify days, the daily traffic demand, i.e., the flow of vehicles vs. time, has to be investigated. Therefore, the flow per minute $J_{\text{nm}}(t)$ of every loop detector $N_{\text{LD}}(t)$ at a certain time t are accumulated. Then the data are summed over all days, where data are available $N_{\text{days}}(t)$, this result is divided by $N_{\text{LD}}(t)$ and $N_{\text{days}}(t)$:

$$J_{\text{dem}}(t) = \frac{\sum_{n=1}^{N_{\text{days}}(t)} \sum_{m=1}^{N_{\text{LD}}(t)} J_{\text{nm}}(t)}{N_{\text{days}}(t) N_{\text{LD}}(t)}. \qquad (1)$$

One advantage of this procedure is the opportunity to analyse even days with an incomplete set of data. The resulting traffic time series are subdivided in seven classes, taking into account the different demand during the weekdays.

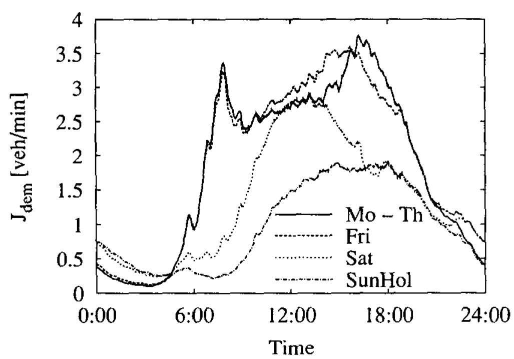

Fig. 5. No. of cars vs. time. The data are stemming from all inductive loops of the network and are averaged over an interval of ten minutes. The four classes are distinct.

Obviously, the demand of many days is quiet similar, since the activity patterns on most working days do not differ very much. However, this is also true if Fridays and days before holidays are compared. Therefore, the number of classes can be reduced. For the decision which traffic time series can be merged into one class a matching process is used which compares the traffic patterns on the basis of an error measure. Finally, the following distinct classes are defined:

- Monday until Thursday, except holidays or days before holidays (**Mo-Th**),
- Friday and days before holidays (**Fri**),
- Saturday except holidays (**Sat**), and
- Sunday and holidays (**SuHol**).

Figure 5 shows the daily traffic demand of these four groups. The highest number of vehicles during one day is generally measured on **Fri**. If this value is set to 100%, the other classes are as follows: **Mo-Th** 97%, **Sat** 71%, and **SuHol** 51%. Analysing the traffic time series in more detail yields for the graph of **Mo-Th** (solid line in Fig. 5) a rough division into four regions:

- a sharp morning peak located at 7:51 with a small standard deviation of three minutes,
- a region which is approximately a straight line but with many fluctuations like the peaks at about 9 or 10 o'clock,
- a peak in the afternoon located at 16:21, which is higher and broader than the morning peak, and
- a relatively smooth curve during the night with a minimum at 3:09.

This classification reflects the daily life, for a detailed discussion see [10].

B. Seasonal Differences

For the analysis of seasonal differences, only working days, i.e., the classes **Mo-Th** and **Fri**, are considered. On average the highest number of vehicles is measured in May. If this value is set to 100% the other months are: June 99%, April and November 98%, March, February and December 97%, September 95%, August and October 94%, July 89%. Most of these differences are due to school holidays. In general, the structure of the traffic demand stays the same during holidays, i.e., traffic patterns are not changed. But in July the absolute values are reduced by 10%. Unfortunately, no data are measured in January during the three years due to problems of the data connection.

C. Special Events

Similar to holidays or long vacations, there are sometimes special events which influence traffic patterns drastically. For this kind of events one example is presented in the following: the solar eclipse at the 11th of August in 1999 during 11:11 to 13:50. In Fig. 6 (a) can be seen that the eclipse influenced the traffic pattern dramatically. From the morning peak until the peak in the afternoon only 93% of the usual number of vehicles is found. The minimum of the dip is located at 12:36 with only 67% of the averaged graph of this class. It is quite remarkable that the solar eclipse influences a whole day.

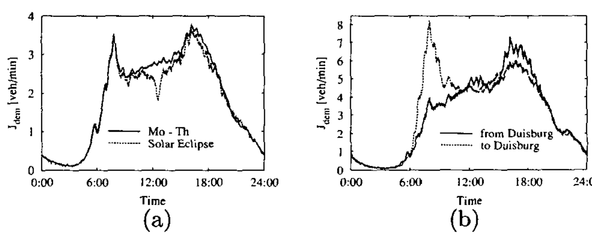

Fig. 6. Different Daily traffic demands. (a) the solar eclipse on the 11th of August influences the whole day and results in a sharp breakdown at 12:36. (b) A flow of commuters can be observed: Into a city in the morning and out of the city in the evening.

D. Dependence on Direction

Up to now, graphs resulting from all inductive loops of the network have been studied. But every street has its own characteristic. Therefore, a single street is selected which exhibits typical commuter flows.

The result for the class **Mo-Th** is shown in Fig. 6 (b). The traffic time series of this street differs strongly from the traffic pattern of the whole network. This is due to a huge number of commuters coming in the morning and leaving in the afternoon. The morning peak is shifted to 7:59. Such data can also be helpful for the identification of the tuning strategies.

E. Automatic Matching

In the previous section, daily and the seasonal differences have been analysed by classifying days. Due to the fact that there are too much inductive loops on the freeway network to analyse every section on its own, in future a method will be used to assign traffic time series in the correct class automatically: matching. In the matching process two sets of data with a certain length N and positive elements x_n, y_n, are compared using different measures of discrepancy. A traffic time series is associated to the sample class with wich the smallest deviation is calculated. There are various measures, which rate the deviations differently. For this process six measurements are used. Two of them are:

- the mean absolute deviation (**MAD**):
- and the mean relative deviation related to the measured value (**MRD**):

The Results are depicted in table I. Some of the data sets are incomplete because the local network was down or the connection to the host system broke off. However, an advantage of the matching process is that even with the a lower number of values a correct matching can be achieved. The results are divided into groups taking into account the number of the measured values.

Since also incomplete data sets are matched correctly, it is possible to automatize the process for forecasts. Measuring data during a few hours of a day allows to decide, which sample graph is suitable to forecast the remaining day.

TABLE I

MATCHING OF 52 DATA SETS OF THE YEAR 2000 WITH THE SAMPLE TRAFFIC TIME SERIES OF THE YEARS BEFORE. SINCE SOME OF DATA SETS ARE INCOMPLETE, THEY ARE SUBDIVIDED ACCORDING TO THE NUMBER OF MEASURED VALUES.

Measure	% of correct matching, x minutes missing				
	x=0	x<240	x<480	x<720	x<1440
MAD	100	100	100	100	100
MRD	100	95	96	97	98

VII. SIMULATION

At the start of every simulation the information of the road network is read from a database. This database comprises the necessary information for the entire network. Thereafter, the on-line connection is established and data is read. These are used to calculate dynamic turning probabilities. Then, the simulation runs for 60 update steps, i.e., 60 seconds. One update step consists of the update of sinks and sources, the exchange of cars between the links, the lane change and the update of the speed and position according to the cellular automaton model. Afterward, the system waits for new on-line information from the inductive loops.

Due to its design, i.e., the discrete algorithm, the cellular automaton approach has proved to be efficient in many applications [13], [14], [15], [16], [17], [18]. Especially, it has been shown that the whole freeway network of Germany can be simulated in multiple real-time [17]. The simulator presented here, runs on a common personal computer 500 MHZ in multiple real-time.

The on-line simulation enables one to interpolate the traffic state between check points and to extrapolate into areas which are hardly or not equipped with detection units. Nevertheless, the simulation results allow for a more detailed examination of the network traffic. In Fig. 7 the number of vehicles and their mean speed during a day is depicted for a Thursday.

The dynamic data like link travel times, densities or velocities, are visualized using a program written in Java (Fig. 8)[1]. Additionally, it can serve as input to intelligent systems [24], [25], [26].

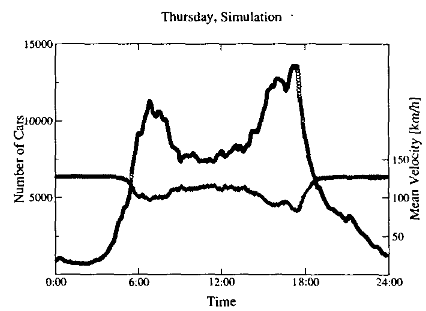

Fig. 7. No. of vehicles and mean velocity vs. time. The simulated data reproduces the specific traffic patterns found in the empirical data (Fig. 5).

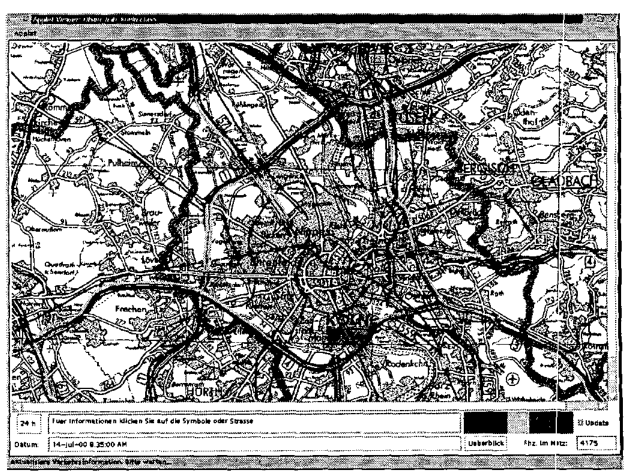

Fig. 8. Screen shot of the visualization of the current traffic state of the area around Cologne.

[1]See: http://www.traffic.uni-duisburg.de/OLSIM for results of the on-line simulation of Duisburg.

VIII. Summary and Outlook

In this paper a framework for performing forecasts with on-line simulations has been presented. The heart of the simulator is a microscopic traffic flow model which is supplemented by the network structure and real-world traffic data stemming from about 3,500 loop detectors of the freeway network of North Rhine-Westphalia.

Besides the model, the network structure has been discussed as well as the simulation techniques, like the vehicle guidance and the tuning strategies, which are used to incorporate real-world data into the simulation. As analysis for forecasts heuristics are used instead of current data. With regard to this a statistical analysis of historical data is presented.

First results of the simulation show that the typical travel patterns in the freeway network are reproduced by the simulation. Additionally, the simulation can be performed in multiple real-time – a basic requirement for a traffic forecast.

Nevertheless, every traffic forecast suffers from a fundamental problem: *the messages are based on predictions which themselves are affected by drivers' reactions to the messages they receive.* Therefore, an anticipatory traffic forecast is necessary, which takes into consideration the reactions and decision-making of drivers [27], [28], [29].

Additionally, more sophisticated models seem to be necessary for a realistic description of freeway traffic [30]. Therefore, we will study the influence of the model in such a huge network in the future. Also the influence of rampmetering in parts of the network will be studied. The framework can also be used as a powerful tool for traffic flow control.

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