A Multi-Agent System for On-Line Simulations based on Real-World Traffic Data

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Abstract

In this paper we present and review a framework for on-line simulations and predictions which are based on the combination of real-world traffic data and a multi-agent traffic flow model. The agent architecture consists of two layers which distinguish the different tasks that road users have to perform. The framework is applied to the urban road network of Duisburg and the freeway network of North Rhine-Westphalia. On the basis of historical data heuristics are derived, which can be combined with the dynamic data of the simulations to provide a short-term traffic forecast. The necessity for an anticipatory traffic forecast, which includes decision-making and route choice behavior of the road users, is discussed.

1. Introduction

Oversaturated freeways and congested main roads in cities reflect the fact that the existing road networks are not able to cope with the demand for mobility which will further increase in future. Especially, in densely populated regions, like the state of North Rhine-Westphalia, it is on the one hand socially untenable to expand the existing infrastructure further in order to relax the situation. On the other hand mobility is a vital good for the economic development of this region.

Therefore, the existing road network has to be used more efficiently using Intelligent Transportation Systems [17, 16]. An integral part of these are Advanced Traveler Information Systems (ATIS) which inform the road user about the current traffic conditions or provide route guidance [1]. The basic requirements for these advises are precise spatially and temporally resoluted data.

These systems work only successfully if the road user is convinced to change his behavior. Basically, there are four different possibilities: the driver can abandon his trip or choose another means of transportation (modal), an alternative route (spatial) or another departure time (temporal). Since most of the road users have certain habits, there must be a personal advantage to change behavior, like a shorter travel time or a more comfortable trip. But it is very unlikely that a road user cancels his trip because it is usually connected with a certain utility , e.g., going to work or enjoying the spare time. One basic condition for a modal change is reliable information about timetables and delays which makes public transportation more attractive. But today, a lot of the road users still use their individual vehicles [14].

The strategy of most ATIS is to change the spatial distribution of traffic patterns, i.e., to provide route guidance. This method is easier than recommending another departure time because in such a case a (short-term) traffic forecast or rather anticipatory route guidance is necessary [7]. In general, information for road users may fall in three categories: historical, current and predictive [5]. Historical data describe the previous states of the network and give insights into the typical travel patterns of the road users. Current information is provided real-time, e.g., by measurement devices. Predictive data reflects expectations and helps the road users to determine optimal departure times for trips.

This paper aims at providing current and predictive data on the basis of simulations and historical data. The outline is as follows: The on-line simulation presented in the sections 2-4 provides current information, i.e., real-time data about the traffic state, like link travel times. The basic framework for an on-line simulation is introduced in Section 2. It is based on the combination of an agent-based model, presented in Section 3, with real-world data stemming from inductive loops. The application of this framework to real road networks is depicted in the following section. In order to provide predictive information, historical data is incorporated into the simulation. In Section 5 historical data is analyzed and used to develop heuristics, the basis of a forecast. In the last section, the impact of such predictive data on the current traffic patterns is discussed and the content is summarized.

2. On-Line Simulations

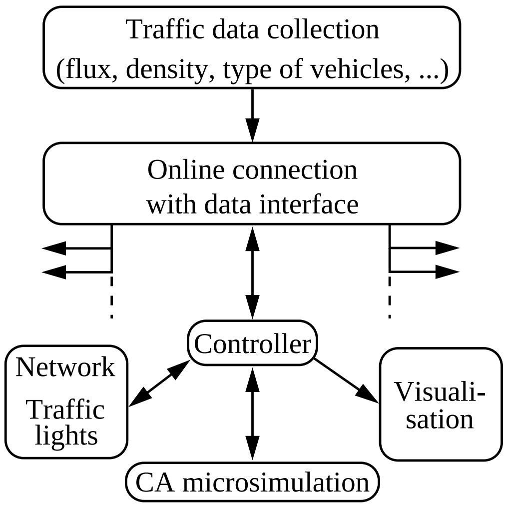

Figure 1. Flowchart of an on-line simulation.

The basis of every intelligent system which helps to alleviate traffic jams is information about the current traffic situation. Typically, traffic data are collected by locally fixed detectors like inductive loops or cameras. Nevertheless, a lot of road networks are not adequately equipped with detection devices to gather information about the present traffic state in the whole network.

A possible way to derive information for those regions which are not covered by measurements is to combine local traffic counts 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. The basic idea of on-line simulations is: *Local traffic counts serve as input for traffic flow simulations to provide network-wide information*.

In Fig. 1 the structure of an on-line simulation is given. The traffic data are sent via a permanent connection to the controller. The controller handles static information like the network structure and performs microsimulations. The results can be visualized and processed in further applications, e.g., Dynamic Route Guidance Systems. An advantage of this approach is the fact that all important entities of the network like its structure or the traffic light management are incorporated directly in the simulation dynamics.

From the description above the basic “ingredients” of an on-line simulation can be identified: a traffic flow model, a digital description of a network, its topology and real-time data. For the applications presented in Section 4 real-time data are available for large road networks.

The model is necessary to perform the microsimulations. Since an on-line simulation requires a high computation speed, a simple and efficient model is inevitable. However, in the following section a general agent-based traffic flow model will be explained which includes a very efficient flow model.

3. Agent-Based Modeling

In general, traffic flow is a complex system consisting of many different road users and their interactions. It can be interpreted as a multi-agent systems (MAS) [8, 33]. MAS-techniques offer a powerful tool to model complex behavior of road users. However, there are only few applications mainly related to the field of logistics and traffic control [11].

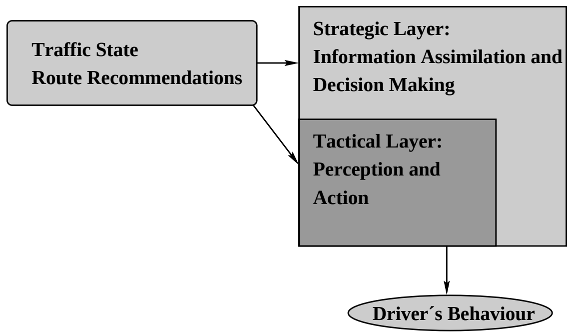

Figure 2. Sketch of the agent driver model.

The activities while driving can be distinguished by two different time-scales (Fig. 2). First, a driver needs to react to the traffic situation, i.e., he accelerates, brakes, or changes the lane. Additionally, he collects information, e.g., traffic messages or route recommendations, which influence in his travel behavior [5].

In order to describe this complex behavior, a two layer agent architecture is proposed in [4]. The layers are responsible for different tasks of the driver. The basic layer is the tactical layer describing the task of driving. The more sophisticated problems, like route choice behavior and navigation are described by the strategic layer.

3.1. Tactical Layer

The tactical layer (Fig. 2) describes the perception and reaction of the driver-vehicle entity on a short time-scale of about one second, the typical reaction time. However, every microscopic traffic flow model describes this layer. In contrast to macroscopic models a driver is identified as basic entity of the system and its behavior, for instance car-following, is modeled in detail.

Traffic flow models used in real-time applications should describe relevant aspects of the flow dynamics as simply as possible. In this spirit the Nagel-Schreckenberg cellular automaton model [25] has been introduced. It represents a minimal model in the sense that it is capable to reproduce basic features of real traffic, like phantom jams but further simplification leads to the loss of this property. So far it has been studied in great detail (for an overview see [9, 30] and references therein). It has also been pointed out that the efficiency of the model allows for high-speed micro-simulations of large-scale road networks [15, 18, 23, 24, 29, 31].

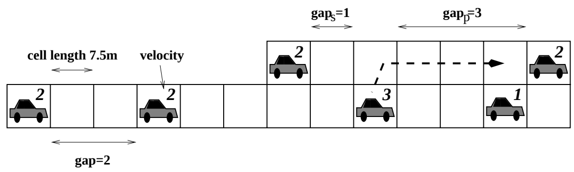

Figure 3. Part of a road in a cellular automaton model.

For completeness, the definition of the model for single lane traffic is briefly reviewed. The road is subdivided in cells with a length of $\Delta x = \rho_{\text{jam}}^{-1} = 7.5$ m/veh, with $\rho_{\text{jam}} \approx$ 133 veh/km the density of jammed cars (Fig. 3). 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!* Such a cellular automaton is deterministic and the stationary state depends only on the initial conditions. But 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.

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. 3. 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 [26].

The cellular automaton can be directly interpreted as a multi-agent system with *reactive (sub-cognitive)* agents. The driver-vehicle entity (agent) reacts to the perception of its own speed and the headway gap. This behavior is rather simple and no cognitive architecture is necessary. Due to its efficiency it allows for large-scale simulations presented in Section 4. But if more complex decision-making processes are considered additional layers have to be introduced.

3.2. Strategic Layer

The strategic layer extends the basic layer and is responsible for the information assimilation and the decision-making of a driver (Fig. 2). During and before a trip, a road user collects information in many ways, for instance by radio broadcast or variable message signs. If the driver has to select between different travel alternatives he uses the collected information and his experience or attitudes. In most models perfect rationality and utility maximization is assumed for such problems. But in real-world scenarios there is no optimal solution to the route choice problem, since the process is highly dynamic and it depends on the behavior of the others.

Additionally, ATISs and other intelligent devices will provide even more information about link travel times, densities, road works, or route guidance in the near future. Thus, drivers have to collect even more information and evaluate it with a higher frequency. This clearly indicates that understanding travelers' route choice behavior is an important consideration for the development and effectiveness of such systems [5].

There are several different techniques to describe such problems [3, 7]. In general, the decision-making process in human beings is based not only on logical elements, but also involves some emotional components that are typically non-logical. As a result, behavior can also be explained by approaches, which additionally consider beliefs, desires or intentions, the so-called BDI-formalism, which is well-known in the field of multi-agent systems.

Such a formalism for a simple commuter scenario is proposed in [4]. The drivers are represented by their individual mental states. One road user trusts in the information, another does not, or only occasionally. Apart from that there is an individual knowledge-base and a certain set of plans. A possible plan could be to leave earlier to avoid being late, another one takes the risk and stays in bed longer. The knowledge base contains for instance navigational information: a driver who is familiar with the network topology has more options for his decisions.

It becomes clear that the description of the strategic layer requires very sophisticated methods and that it is crucial for development of intelligent transportation systems. The starting point is the understanding of the human behavior [2]. Note in the applications discussed in the next section a simplified representation of the strategic layer is chosen. The strategic layer is more important if predictive information is considered (Section 5).

4. Network and Data

In Section 2 a framework for providing real-time data to the road user was proposed. It is based on the combination of real-world traffic data with simulations using a traffic flow model. In the following we present two examples for such networks: the urban traffic of downtown Duisburg and the freeway network of North Rhine-Westphalia.

4.1. OLSIM Duisburg

An urban road network has a complex structure, but Esser and Schreckenberg [15] showed that arbitrary kinds of roads and intersections can be constructed with only a few basic elements. As an example the road network of downtown Duisburg is shown in Fig. 4. The so-called check points are marked as filled circles and sources or sinks are identified by letters. At the check points the data of all lanes of a road are available. Here the local flow can be tuned with respect to the empirical data.

In the following the network is described: 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 signal control and the detailed priority rules are included into the simulation. The network consists of 107 nodes (61 signalized, 22 non-signalized and 24 boundary nodes), 280 edges and 22,059 cells corresponding to about 165 km. The boundary nodes are the sources and sinks of the network [31].

For the on-line simulation the agent model has to be supplemented by traffic data gathered from detection units distributed all over the city. Every minute the measurements of about 350 inductive loops (approx. 4 kBytes) are sent from the traffic computer of the municipal authority of Duisburg

Figure 4. Sketch of the simulated road network.

to the on-line simulation computer (Fig. 1). These data are used to calculate *turning probabilities* and to tune the simulation which will be explained later on.

There are different strategies to run a micro-simulation in such a network. On the one hand one can use origin-destination (OD) 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 agents do not follow a predefined route. Instead, they choose their way at every node according to turning probabilities computed using real traffic data. This is a very simple implementation of the strategic layer (Section 3.2) and more sophisticated methods are necessary in order to provide a traffic forecast (Section 6.1).

Currently, turn counts can be derived directly for 56 driving directions. In addition, the turning probabilities were completed by manual counts in order to get at least the average number of turning vehicles at crossings which are not covered by measurements.

For realistic results it is crucial to incorporate the real-world data in the simulation without perturbing the dynamics which are present in the network. To adapt the simulated results to the real-world data we additionally introduce so-called *check points*. They are located at those places where a complete cross-section is available, i.e., all lanes are covered by an inductive loop (Fig. 4). At such places, it is convenient to perform adjustments. The last minute's results of the simulation have to be compared with the measured data. This can be done using different methods [18]. The simplest one used in urban traffic is the so-called sink- and source strategy: Every check-point consists of a sink at the beginning and a source at the end. The incoming vehicles are deleted at the sink and the source adds the measured number of vehicles.

Due to its design the cellular automaton approach allows to simulate a network much faster than real-time – a basic requirement for on-line simulations and *traffic forecast* [23, 29, 15, 24, 18]. On a common personal computer (Pentium 500 MHz) it takes 5 minutes to simulate the traffic of a whole day in the network. Besides, it is possible to interpolate the traffic state between check points (which are typically nearby intersections) and to extrapolate into areas which are hardly or not equipped with detection units. Additionally, the simulation provides dynamic data, e.g., link travel time or traffic densities. These data can be visualized [1] and also serve as a support for planning a trip. For instance, the data can be processed by route guidance systems which allow the road users to organize their trips with regard to individual preferences [32].

4.2. Freeway Network North Rhine-Westphalia

In the previous section a simulation framework for urban traffic has been discussed. In general, urban and freeway traffic differ in some aspects. The traffic dynamics on urban roads are governed by the intersections, mainly traffic lights, whereas on freeways dynamic phases, e.g., synchronized flow or stop-and-go traffic emerge (for an overview [19, 20]). The analysis of single-vehicle data [28] yields that for freeway traffic a more detailed description of the dynamics seems to be necessary [22].

Another difference is the location of sinks and sources in the network. In urban areas, they are located nearly everywhere, because a vehicle can leave the system to go to a parking area or just stop on the sidewalk. In freeway networks, the sinks and sources are clearly defined, namely the on- and off-ramps. This makes a traffic forecast easier if flows on the ramps are available.

The application described below is based on the freeway network of North Rhine-Westphalia, an area of about 34,000 km^2. The roads of the network have a length of 6,000 km. There are 67 highway intersections and 830 on- and off-ramps. The digital version of the network consists of 3,560 edges and 1.4 million sites. Similar to urban areas [15] the topology of the network was constructed using basic elements, namely main tracks and transfer tracks [18]. To provide precise travel times the length of every piece of topology, especially transfer tracks, was determined using a Geo-Information System (GIS) [2].

Currently, data from about 2,500 inductive loops are accessible. Every minute the aggregated amount of cars and trucks as well as their velocities are sent via permanent lines from the traffic control centers in Recklinghausen and Leverkusen to the controller of the simulation. Results for the on-line simulation are depicted in Fig. 5, where the number of vehicles vs. the time for a part of the freeway network are shown. The data are generated by an on-line simulation and basic features like the rush-hour peaks are recovered.

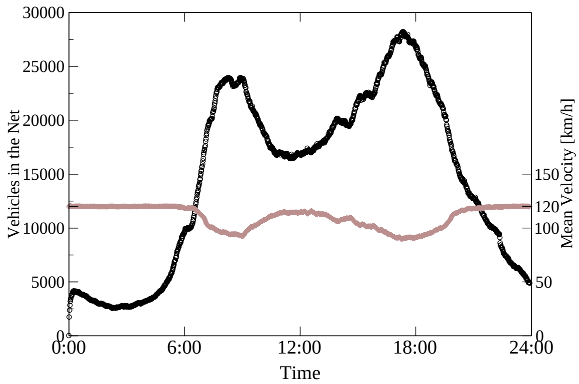

Figure 5. Number of vehicles vs. time.

In future, it is planned to generate traffic messages using such a system. Nowadays, messages are given in form of jam length, which is not a very good measure. For instance, a jam of length 3 km can have different impacts, since it might be the beginning of a road blockage or only a small disturbance. We aim at giving measures, like the travel time or the travel time loss in a jam. These provide a decision support for the road user to plan a trip more efficiently.

5. Forecast

In the previous sections the on-line simulation, which provides current data, was presented. In this section one way to generate predictive information is discussed. However, there are many different approaches for predicting short-term traffic conditions, e.g., time series analysis [35], neural networks [12, 13], and tracing of jams [21]. Employing the on-line simulation described in the previous section, predictive data can be generated using the dynamics of the current traffic state, i.e., continue the simulation without

[1] The current traffic state of Duisburg is published in the Internet every minute (`http://www.traffic.uni-duisburg.de/OLSIM`).

[2] The basis of the GIS is the NW-SIB provided by the state of North Rhine-Westphalia.

current traffic data. This is a “do-nothing” scenario: the assumption is that the data does not change. Nevertheless, the network looses vehicles at the boundaries and off-ramps. Therefore, predictions about vehicles entering the network at the boundaries and on-ramps have to be made. These can be based on heuristics, i.e., experience about recurrent events, which are derived by a statistical analysis of historical data.

5.1. Heuristics based on Historical Data

In order to develop heuristics for a traffic forecast, we analyze historical data of the inner city of Duisburg (see Section 4.1). In the year 1998, 228 inductive loops supplied data for 186 days. In 1999, the network was extended and 351 loops supplied data for 106 days. To compare the data from different years these are given in cars/inductive loop and minute [10].

In order to classify differences, the daily traffic demand, i.e., the flow of vehicles vs. time, are investigated (Fig. 6). Note that the graphs reflect the traffic pattern of the whole network, since the value given is the number of cars measured averaged over all inductive loops.

In general, two different time-scales for changes can be distinguished: daily and seasonal differences. Seasonal differences arise due to school holidays. Daily differences are there because on working days a sharp morning peak is there which is absent on Sundays or holidays. In Fig. 6 the results of a statistical analysis are shown. In order to classify different days, the daily demands of them are compared with each other. It is quite obvious that the activities on most working days do not differ very much. Interestingly, this is also true if Fridays and days before holidays are compared. The data used are stemming from all inductive loops of downtown Duisburg (Section 4.1) and are averaged over an interval of ten minutes. There are four classes of days that can be easily identified. Additionally, there are sometimes special events, like football games. Thus, the following distinct classes can be defined (Fig. 6):

1. Monday to Thursday, except holidays or days before holidays,
2. Friday and days before holidays,
3. Saturday except holidays, and
4. Sunday and holidays.

The daily graphs of these classes are depicted in Fig. 6. The most cars are generally measured on Friday. If this value is set to 100% the other classes are as follows: Monday to Thursday 96%, Saturday 71%, and Sunday 51%. If the daily graphs are analyzed in more detail, the graph for Monday til Thursday (solid line in Fig. 6) can be roughly subdivided: a sharp morning peak (7:49 a.m, with a standard deviation of 5.5 min), a high traffic volume during the day, a peak in the afternoon (at 4:26 p.m. with a standard deviation of 26 min), and light traffic at night.

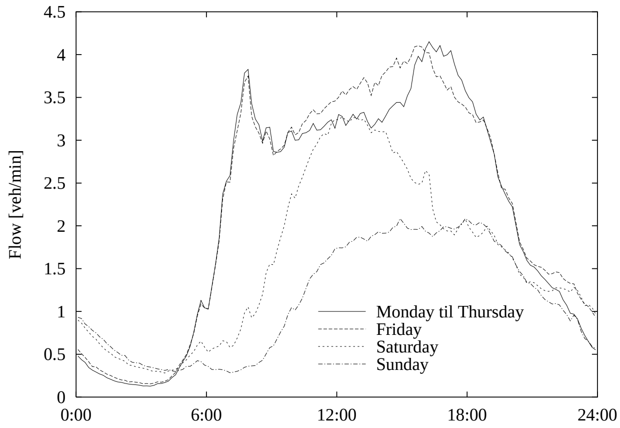

Figure 6. Number of vehicles vs. time.

This division reflects the daily life. In the morning, people go to work at about 8 o’clock. Since most of the people begin to work roughly at the same time this peak is much sharper than that in the afternoon. Albeit, the afternoon peak is much higher since in addition to the commuters there is shopping traffic. Besides this global features, there are smaller peaks which are recurrent. In the morning two peaks are found, the first morning shift at 5:45 a.m. and the second morning shift at 6:54 a.m., with very small standard deviations of about five and four minutes, respectively. These peaks result from the shift workers of the heavy industry in this region.

For a traffic forecast the standard deviations of the peaks are an important feature. They reflect the quality of the heuristics. Since the standard deviation of the morning peak is about six minutes, it will appear with a high probability in an interval of this small span.

For the analysis of seasonal differences, only the data of 1998 can be used. In 1998, data are available from February to November. On average the highest number of vehicles was measured in May. For this comparison only working days, i.e., Mondays to Fridays, are included. If the value for May is set to 100% the other months are: November 99.1%, June and September 97.9%, March and April 97.7%, February 97.2%, August 94%, October 89.91%, July 88.42%. Most of these differences are due to school holidays. In general, daily graphs during holidays stay the same, i.e., the traffic patterns do not change. But in July the absolute values are decreased by 10%. Of course, the analysis was only carried out during one year and is therefore not statistically profound. Today, the data base for the freeway network is too small to carry out such an analysis. But it will be done in future. However, the travel patterns in the urban area will show a lot of similarities since the freeway network is closely linked to the urban network.

With this kind of statistical analysis, it is possible to classify special events or even local origin-destination matrices [10]. In addition to the simulations described above, these heuristics can be used to predict the temporal evolution of traffic patterns at local points of road networks, e.g., boundary nodes and on-ramps. Thus, predictive data is calculated by linking current (on-line) with historical data.

6. Outlook

In the previous section, we have discussed possibilities to generate current and short-term predictive data. Although such information services have reached a high technical standard, the reaction of the road user to these systems is not well explored. Recommendations and information will be given to the road user by means of communication such as variable message signs or radio broadcasts. But each of these systems is confronted with a fundamental problem: *the messages are based on future predictions which themselves are affected by drivers' reactions to the messages they receive* [7]. Therefore, an anticipatory traffic forecast, which anticipates the reaction of the road users to the information is necessary.

6.1. Anticipatory Traffic Forecast

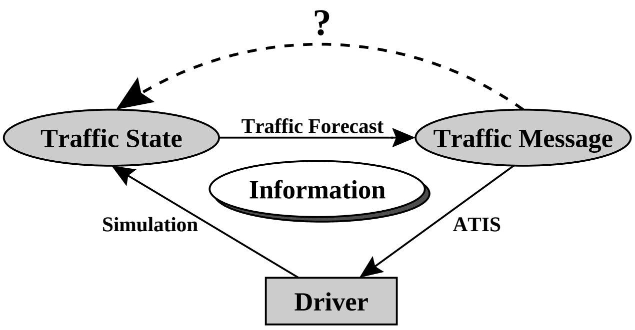

Figure 7. Impact of a traffic message.

In Fig. 7 a feedback loop is depicted, which describes the effect of dynamic information in traffic networks. First, the current traffic state is generated using on-line simulations. Then algorithms are used to provide additionally predictive data. The results are traffic messages, which are transmitted to the driver using, e.g., Advanced Traveler Information Systems (ATIS). The road user receives and processes the information and then changes his plans with regard to the new input. The feedback loop is closed.

The effect of this travel behavior on the current traffic state needs to be evaluated using a simulation. The most important question is: what is the impact of a traffic message? Today, this feedback is not very strong since the information about the traffic state is not precise enough. Once a road user has chosen a certain route he will rarely be able to evaluate the other alternatives. But reliable information, which might be available soon, can lead to social dilemmas, i.e., situations where there is a conflict between individual and collective aims [6].

To provide an anticipatory traffic forecast, the reasoning and reaction of the drivers has to be included in the agent model described above. Bottom et al. [7] propose a framework in which every road user behaves rationally and thus, a fixed point problem has to be solved which is equivalent to finding one Nash equilibrium. From experimental game theory it is known that people exhibit bounded rationality and a system rarely reaches such an equilibrium [27]. In [3, 34] binary route choice scenarios with information are studied. It is found that dynamic information, e.g., link travel time, can harm traffic patterns significantly. For an anticipatory traffic forecast it is therefore necessary to describe the decision-making of a road user in detail by, for instance, employing multi-agent techniques (Fig. 2).

6.2. Summary and Conclusion

This paper discusses an Advanced Traveler Information System and its impact on traffic patterns. Using real-world traffic data stemming from inductive loops and an agent-based traffic flow model it is possible to derive the traffic state of a complete network on-line. With a statistical analysis of historical data it is possible to develop heuristics which allow for a traffic forecast.

The multi-agent model presented has a two layer architecture: the tactical and the strategic layer. The tactical layer describes the task of driving and corresponds to a microscopic traffic flow model, e.g., the Nagel-Schreckenberg cellular automaton. The strategic layer is responsible for the information assimilation and the decision-making.

Using this model it is possible to perform on-line simulations of urban and freeway networks, the downtown area Duisburg and the freeway network of North Rhine-Westphalia. The results are published in the Internet every minute. The dynamic data produced, e.g., link travel times or traffic densities can be processed in dynamic route guidance systems. For both networks simulations are performed faster than real-time – a basic requirement for a traffic forecast.

A naive approach to traffic forecast is a "do-nothing" scenario. The the dynamics of the traffic flow model are used to run the on-line simulation without further data support. But in the system, vehicles leave at the boundary nodes and the network grows empty. Therefore, it is necessary to develop heuristics which provide experience about the temporal evolution of the traffic patterns. These are extracted from historical data.

In general, it is found that the days of the week can be classified in four groups: Monday to Thursday, Friday, Saturday, and Sunday. Also seasonal differences which result from school holidays can be distinguished. But every traffic forecast suffers from a fundamental problem: *the messages are based on future predictions which themselves are affected by drivers' reactions to the messages they receive*. Therefore it is necessary to provide an anticipatory traffic forecast which includes the reasoning and decision-making of the individual drivers. In general, human factors in Intelligent Transportation System are not well explored. Within the research project SURVIVE we will perform route choice experiments with real road users and analyze them with methods of experimental economics[3].

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