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The impact of real-time information in a two-route scenario using agent-based simulation

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Abstract

Since advanced traveler information systems (ATIS) have been introduced, their potential benefits as well as their drawbacks have been discussed controversially. This will continue as long as the drivers' reactions upon current or even predictive information about the traffic situation are not known. Thus, traffic models that also consider this feedback are necessary. In this paper, we address a basic two-route scenario with different types of information and study the impact of it using simulations. The road users are modeled as agents, a natural and promising approach to describe them. Different ways of generating current information are tested. It is pointed out that the nature of the information very much influences the potential benefits of the ATIS.

Keywords: Advanced traveler information systems; Multi-agent systems; Route choice behavior; Simulation; Cellular automaton

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1. Introduction

In the recent decades, Intelligent Transportation Systems were developed aiming at improving the travel efficiency and mobility, enhancing safety and thus providing economic and environmental benefits. An integral part of these are advanced traveler information systems (ATIS) that provide current or even predictive information about the traffic flow to the road users (Adler and Blue, 1998, ITS International 1999).

Although such systems have reached a high technical standard and have a high potential to alleviate traffic congestion, the impact of the systems on traffic patterns is not known to a sufficient extend (Ben-Akiva et al., 1991; Bonsall, 1992; Hall, 1996; Dia and Purchase, 1999; Bottom et al., 1999; Wahle et al., 2000a; Mahmassani and Jou, 2000). Furthermore, some phenomena or behavior patterns are observed that may disprove the benefits of the given information. In (Ben-Akiva et al., 1991) the following three phenomena are listed:

- *Oversaturation*: ITS can offer a huge amount of information to the user. But if people are confronted with too much information, they are oversaturated, tend to ignore the information and develop simple heuristics to solve the problem. Therefore, especially ATIS should offer personalized information (Adler and Blue, 1998).
- *Overreaction*: A more fundamental problem is the overreaction, which occurs if too many drivers respond to the information. Suddenly, a congestion may be transferred from the original area to the alternative routes. People start to anticipate the behavior of the other drivers'. This anticipation gets even worse if predictive information is given. Thus, the behavior of the drivers has to be incorporated in the forecast (Bottom et al., 1999; Wahle et al., 2000a). Otherwise, this behavior might cause oscillations of traffic flow among the alternatives, since fast routes attract traffic and, in the process, become slower, whereas the previously slower ones turn faster (Ben-Akiva et al., 1991; Bonsall, 1992).
- *Concentration*: A set of drivers who go from one origin to one destination tend to use different routes, since they have different preferences or perceive the situation in different ways. This leads to a natural distribution among the routes. ATIS can reduce these variations if all the drivers use the objective information broadcasted. As a result a greater number of them may select the best alternative and consequently drivers with similar preferences will choose the same route, leading to congestion on this (Arnott et al., 1991; Wahle et al., 2000b).

Although the effects of overreaction and concentration are similar, the nature of both phenomena is different (Ben-Akiva et al., 1991). Concentration is intrinsic to any system with information, whereas overreaction is a consequence of the fact that drivers cannot forecast the behavior of the others. However, as intelligent devices will provide even more information about link travel times, densities, or route guidance to the road user, this ability will be crucial for the utility of the ATIS. Therefore, understanding travelers' route choice behavior is an important consideration for the development and effectiveness of such systems (for an overview, see Ben-Akiva et al., 1991; Bonsall, 1992; and Mahmassani and Jou, 2000).

Many classical microscopic traffic flow models lack the description of this kind of behavior. Therefore, multi-agent systems are introduced as a new modeling paradigm. They offer a natural way to model even cognitive behavior of road users. In this work, we try to model the impact of real-time information on the traffic patterns using an agent-based model. Special attention is paid to study different kinds of information and their specific impact on the traffic patterns.

The remainder of this paper is structured as follows: In the next two sections we will sketch some basic notions of agent-based systems and microscopic traffic flow models. After that, we will merge these approaches into an agent-based traffic model especially describing a simple two-layer driver model that is used to examine different types of information and their impacts in a two-route scenario. This scenario is presented in Section 5. In Section 6 the results of our simulation experiments are presented and discussed in detail. The paper closes with a summary and an outlook to future work.

2. Agents in the traffic domain

In general, traffic systems, like urban traffic or pedestrian crowds, consist of many autonomous, intelligent entities, which are distributed over a large area and interact with each other to achieve certain goals. These entities may be completely different: traffic lights, trucks or even road users, but all of them are changing actively the situation the traffic system is in. This is one of the major characteristics assigned to "agents".

However, there exists no general definition of an agent. It can represent an autonomous entity which is situated in an environment and interacts with the latter including other agents to achieve its individual goals (for an overview see Franklin and Graesser, 1997; Wooldrige and Jennings, 1995). Basically, two extreme kinds of agents can be identified: reactive and cognitive agents. A reactive agent only maps the possible perceptions to the reactions e.g., simple *stimulus-response systems*. Such simple agents can be used to describe car-following behavior (Brackstone and McDonald, 2000 and references therein). A cognitive or deliberate agent is endowed with reasoning capabilities for planning or other knowledge-based tasks.

The behavior of reactive agents is often described using rules (Russell and Norvig, 1995), just linking a perceived situation with appropriate action. For solving or modeling more knowledge-based tasks different agent architectures were proposed. Prominent examples are BDI architectures (Haddadi and Sundermeyer, 1996; Rao and Georgeff, 1991).

In this architecture, behavior is described based on three mental categories: *beliefs*, *desires* and *intentions*. Beliefs form the agents' current knowledge about the environment and its dynamics. This information can be gathered by previous experience and may not be correct. The desires describe the motivations of the agent—in form of more or less abstract goals. Intentions on the other side are often almost executable plan fragments that are selected, configured or used for planning based on the current beliefs and desires of the agent. BDI architectures are not only relevant for problem solving but—as they are based on the cognitive theory of intentional systems—they are also important for modeling entities with cognitive abilities.

A conceptual framework for modeling drivers' behavior in traffic simulations that combines concepts from describing intentional systems with reactive behavior is presented in (Burmeister et al., 1997). Every agent is characterized by its goals, resources, and behavior. The architecture comprises five modules: effectors, sensors, communication, intention and cognition. The effectors, sensors and communication modules make contact with the outside world. The intention module represents the agent's long-term goals, whereas the cognition is the "heart" of the agent. It comprises knowledge, a problem-solver and a cooperation component. The problem-solver evaluates the sensor data and selects among the possible actions with respect to the intention. Other approaches for using agent-based concepts—especially the BDI-framework—in driver models can be found in (Bazzan et al., 1999; Rossetti et al., 2000).

A system of interacting agents is called a multi-agent system. In such systems additional properties can be identified which go beyond the properties of a single agent (Jennings et al., 1998). The agents have only a limited view of the whole system and they possess only incomplete information or capabilities to solve problems. In multi-agent systems the data are kept local, i.e., the internal status of the agent is not known to all other agents. In the ideal case the agents act in an asynchronous manner. Another characteristic is that no central control system is found, which governs all agents. These properties hold in a traffic system, like the drivers in a road network.

Applying multi-agent system technology in traffic systems is not new. Multi-agent systems provide a powerful method for specifying such systems, since they offer a simple, intuitive way to describe every autonomous entity on the individual level. Prominent applications are for instance: in an urban traffic scenario, traffic lights and control centers can negotiate for achieving the best signal plan for a road network (Cuena et al., 1995; Bazzan, 1997; Ossowski, 1999). Because of the inherent distributed nature, the dynamics and uncertainty in the setting, transport planning and control are highly promising areas for multi-agent system technology (Fischer et al., 1995; Lind and Fischer, 1999; Bürckert et al., 2000) in general.

3. Microscopic traffic flow models

The concept of an agent is well suited for the description of road users in traffic scenarios. [4] They are autonomous entities which are situated in an environment, adapt their behavior to the dynamics they perceive (reactive), interact with other agents (social) in order to achieve a specific goal (rational). The road user permanently perceives information via sensors, then reasons about it, makes a decision, and acts on the environment via effectors. This insight is not completely new, but it offers an alternative interpretation of classical traffic flow models as well as the development of more general and effective frameworks to model driver behavior on a cognitive level.

In general, microscopic traffic flow models describe the act of driving on a road, i.e., the perception and reaction of a driver on a short time-scale. In these models, the road users are the basic entities and their behavior is described using several different types of mathematical formulations. *Car-following* models for instance describe the motion of the vehicle, based on the basic principles of classical Newtonian dynamics (for an overview see Brackstone and McDonald, 2000). In *particle-hopping* models the environment is subdivided in cells, i.e., discrete. This is done using the language of cellular automata (Nagel and Schreckenberg, 1992).

Nevertheless, any microscopic traffic flow model can be interpreted as a multi-agent system comprised of reactive or sub-cognitive agent (Bazzan et al., 1999; Burmeister et al., 1997; Hidas, 2000; Rossetti et al., 2000). In order to test the feasibility of such an interpretation and to point

[4] Note that throughout this work, the terms vehicle or driver are used to describe the driver–vehicle object.

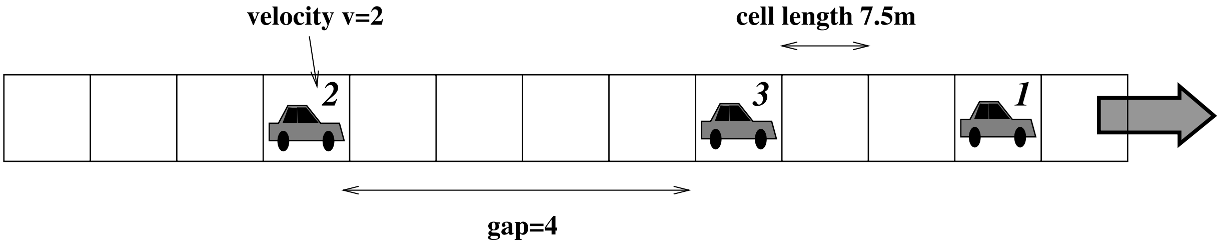

Fig. 1. Part of a road in a cellular automaton model. Each lane is subdivided into cells of a length of 7.5 m. Every vehicle has a certain speed v.

out the potential of such an approach, we discuss an example in greater detail: the standard cellular automaton proposed by Nagel and Schreckenberg (1992).

Traffic flow models should describe relevant aspects of the flow dynamics as simple as possible. In this spirit, the Nagel–Schreckenberg cellular automaton model (Nagel and Schreckenberg, 1992) 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. If it is further simplified it loses this property. So far it has been studied in great detail (for an overview, see Chowdhury et al., 2000 and references therein).

In the following, 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. 1). 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: $v_i' \leftarrow \min(v_i, \text{gap})$.
R3 Randomizing: with a certain probability p_{dec} 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 $\Delta t \approx 1$ s, the typical time a driver needs to react.

Every driver described by the Nagel–Schreckenberg model can be seen as a reactive agent. He is autonomous, situated in a discrete environment (Fig. 1), and has (potentially individual) characteristics: its maximum speed $v_{\max}$, and the deceleration probability p_{dec}. During the process of driving, he perceives information the distance to the predecessor gap and his own current speed v. This information is processed using the three rules (R1–R3) and changes in the environment are made using rule R4. The first rule describes one goal of the agent, he wants to go by maximum speed $v_{\max}$. The other goal is to drive safe, i.e., not to collide with its predecessor R2. In this rule the road user assumes that its predecessor can brake to zero speed. However, this is a very crude approximation of the perception of an agent. These first two rules describe deterministic behavior, i.e., the stationary state of the system is determined by the initial conditions. But drivers do not react in this optimal way: they vary their driving behavior without any obvious reasons. This uncertainty in the behavior is reflected by the braking noise p_{dec} R3. It mimics the complex interactions with the other agents, i.e., the overreaction in braking and the delayed reaction during acceleration. Finally, the last rule is carried out, the agent acts on the environment and moves according to his current speed.

The behavior described by the Nagel–Schreckenberg model is rather simple, the agent reacts to the situation in a simple stimulus-response pattern. On the one hand, this is effective since the aim of the cellular automaton approach is to provide a very simple model capable of high-speed simulations. On the other hand, one should be clear about the limitations of the approach: the driver does not have a memory, and can only plan ahead the next second. Thus, they are not able to learn from past experience—all knowledge they possess is procedural (Hidas, 2000). However, for describing only the movement this is not a problem. In order to describe more complex rule-based behavior e.g., multi-lane traffic, merging regions, traffic lights, the set of fundamental rules has to be expanded (Nagel et al., 1998; Esser and Schreckenberg, 1997).

4. A driver model based on a two-layer agent architecture

As discussed in the previous section, the classical microscopic traffic flow models describe fully automated activities. They are used for modeling and simulating vehicular motion in road networks e.g., for on-line simulations (Esser and Schreckenberg, 1997; Schreckenberg et al., 2001). For more complex applications, knowledge-based behavior needs to be modeled in addition. Examples are frameworks for transportation planning and traffic assignment (Nagel et al., 2000), where activities and choice of transportation of potential road users have to be modeled at a large scale. Another example is tackled in the following: estimation of the impact of an intelligent transportation system (ITS), that considers both route choice and actual driving. Hereby, there is a strong need to model knowledge-based behavior, especially the agents decision-making and information assimilation.

The starting point of this work is a two-layer architecture for describing the road user (Bazzan et al., 1999; Wahle et al., 2000a). The basic idea is to distinguish the activities associated with the task of driving by different time-scales and complexity (Fig. 2):

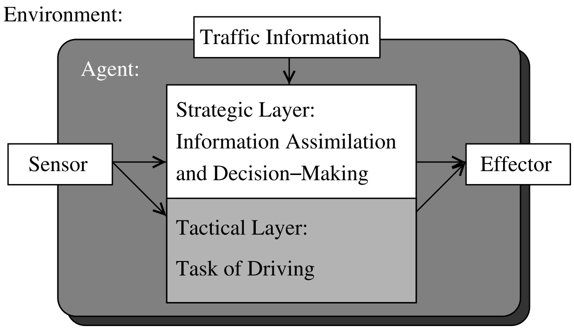

Fig. 2. Sketch of the agent. The agent receives information via the sensors, and processes it in the tactical or the strategic layer depending on its complexity. It is situated in an environment, perceives information, i.e., the *gap* and its own speed, through a sensor, processes this information in a reactive way and acts on using the effector.

- The basic layer is the tactical one describing the task of driving, i.e., accelerating, braking, or changing the lane.
- The more sophisticated problems, like route choice behavior and navigation are described by the strategic layer.

In summary, the two layers are responsible for the different tasks of the driver. In a model which deals with decision-making and information assimilation, both layers are necessary: the basic layer and the actual driving is responsible for evaluating route choices and thus generates the information processed by the strategic layer. In the following, the two layers are explained in more detail.

4.1. Tactical layer

The tactical layer (Fig. 2) describes the perception and reaction of the driver–vehicle entity on the short time-scale of about 1 s, the typical reaction time. It is the level of actual driving and on route behavior. Therefore, this layer can be represented by a microscopic traffic flow model flow (as described in Section 3): tactical driving behavior is purely reactive, as the perceived gap to the next car is directly used by the agent to determine his own speed. According to the Nagel–Schreckenberg model an additional braking noise abstracts individual distractions, etc. speed is the only factor that determines the agents movement. Simulating these movements, the current speed of every agent is depending on other agents on the same route. Finally, the actual driving time on that route for an individual agent is traced. This information forms the basis for the evaluation of the traffic situation processed on the strategic layer.

4.2. Strategic layer

The strategic layer extends the former one and is responsible for the information assimilation and decision-making of a driver (Fig. 2). In the application described here, this layer is responsible for route-choice behavior, but other knowledge-based tasks are also thinkable. During and before a trip, a road user collects information in many ways, for instance by radio broadcast or VMS. If the driver has to select between different travel alternatives, he uses the collected information according to his experience or attitudes.

As described in Section 2, the BDI-formalism is especially apt as a framework for describing the decision-making process of intentional agents, like simulated human beings. On the other side, these cognitive processes are not only based on logical elements, but also involve some emotional components. These are especially important in modeling behavior in traffic situations, where, e.g., no direct negotiations between actual rational agents can happen due to the necessary short reaction time, and to the lack of means for e.g., telling the driving in front to speed up. Thus a generic BDI-architecture—as used in multi-agent technology—has to be also filled with emotional factors. That makes the concept and implementation of such a driver model sophisticated and costly.

In the following, a very restricted form of a strategic layer was used. It is just tackling route choice at the beginning of a trip. Hereby an agent processes the information provided by a traffic information system based on his general attitude e.g., concerning his trust in traffic messages.

Desires and intentions are not represented explicitly, as it is not necessary in the simple two-route scenario described in the following section. However, the two-layer architecture provides the possibility to extend the driver model directly when the necessity is assessed.

5. Two-route scenario

In the following, a scenario with two routes, which is based on the model described in Section 4, will be introduced. Suppose that there are two routes A and B with the same length, i.e., the number of cells L is identical (Fig. 3). With a constant rate α road users enter the system and thus have to choose between the two alternatives. In order to study the impact of information on traffic patterns, dynamic data has to be generated by simulations. The process of generating the data will be discussed later. In the literature, this scenario is a standard one used to study the impact of ATIS like for instance in (Bonsall, 1992; Hall, 1996). In general, two types of road users are identified: *static and dynamic ones.*

5.1. Static agents

Static agents can be either those non-equipped with in-vehicle devices, or those who just ignore the dynamic information like those not reading information boards or not listening to the radio. Therefore, these agents decide on the basis of static information e.g., the length of the routes or road signs. In the simulation experiment this is represented by the variable p_{AB}, i.e., the probability that a static driver chooses the route A.

5.2. Dynamic agents

Dynamic drivers process the information equipped with ATIS or other devices. In this scenario, information is displayed on a board (Fig. 3). The board can represent a message sign at the

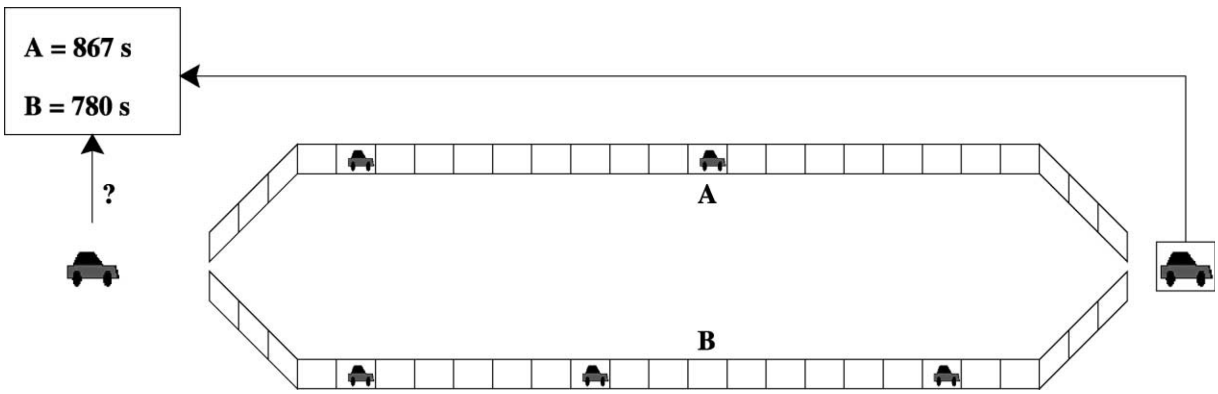

Fig. 3. Traffic scenario with dynamic information. Agents entering the system have to select a route comprising L cells. Static drivers choose their route with a probability p_{AB}, whereas dynamic drivers decide with regard to the information displayed on the board like for instance the travel time. The information is transmitted to the board by the FCs when they leave the routes.

beginning of the routes or an in-vehicle device. Using this information a dynamic driver always tries to optimize his trip, i.e., he selects the route with the minimal travel time. In that sense he behaves "rationally". Note that this is a very particular kind of rationality: the agent trusts the information on the board and decides on the basis of it. He does not *over-react*, i.e., there is no reasoning about the behavior of the others. If the information for both routes is the same, a route is chosen randomly. The amount of dynamic drivers is represented by the variable s_{dyn}. After the route choice process, both kinds of vehicles behave in the same way (i.e., driving on the route according to the rules established in the tactical level).

5.3. Generation of dynamic data

The basis of the decision of the dynamic agents is the real-time information. This can for instance be provided by *floating-cars* (FCs). FCs are employed to investigate traffic conditions on the routes e.g., to measure speed or link travel times. In this work, we study different kinds of information. In the first scenario described, the FCs transmit their travel times to a board upon leaving the system (Fig. 3). Thus, they generate dynamic traffic information, which is the basis of the route decisions of new vehicles entering the system. The amount of FCs is represented by the variable s_{FC}. The remaining vehicles do not transmit information. However, different quantities of information, like average speed or density on the route, can also be studied.

5.4. Simulation technique

The simulations are performed in the following way: at the beginning, both routes are empty and the information on the board is set to a default value e.g., $t_{\mathrm{A}}, t_{\mathrm{B}} = L/(v_{\max} - p)$. Note that this is the travel time on free routes, since the velocity in the free-flow region is about $v_{\max} - p$. Dynamic drivers choose their route at random, while static drivers do this with regard to p_{AB}. With the probability s_{FC}, a static or dynamic driver is generated as a FC. After a certain time, FCs finish their trips and transmit their travel times to the board. Now, the dynamic drivers decide on the basis of the information available on the board. In general, every simulation lasts for 50,000 time-steps. For the analysis, the first 5,000 steps are ignored. The results of a typical experiment are depicted in Fig. 4.

Because of the model employed, special care has to be taken when injecting new vehicles on the routes. Open systems are characterized by an injection rate α and an extinction rate β, i.e., a vehicle enters the system with the probability α or leaves it at the end with the rate β. For convenience, we set $\beta_{\mathrm{A}} = \beta_{\mathrm{B}}(t) = 1$ and $\alpha = 1$. For the injection rates of route A and B, the following relation holds: $\alpha_{\mathrm{A}}(t) + \alpha_{\mathrm{B}}(t) = \alpha$, with $(\mathrm{d}/\mathrm{d}t)\alpha_{\mathrm{A}}(t) \neq 0$ and $(\mathrm{d}/\mathrm{d}t)\alpha_{\mathrm{B}}(t) \neq 0$. The time dependence represents the dynamics of the decisions.

The process of injection is carried out in the following way: the first $v_{\max} + 1$ cells of every route is the injection area. For adding a vehicle, the position of the first car on the route is determined. The new vehicle is put into the injection area with a minimum gap of $v_{\max}$ to the detected car, and a speed of $v_{\max}$. Then the update is carried out, if a vehicle remains in the injection area it is deleted. This procedure is necessary to avoid jams short after that area, since otherwise the injection rate is replaced by the flow out $\alpha = j_{\mathrm{jam}}$ and high-flow rates cannot be established.

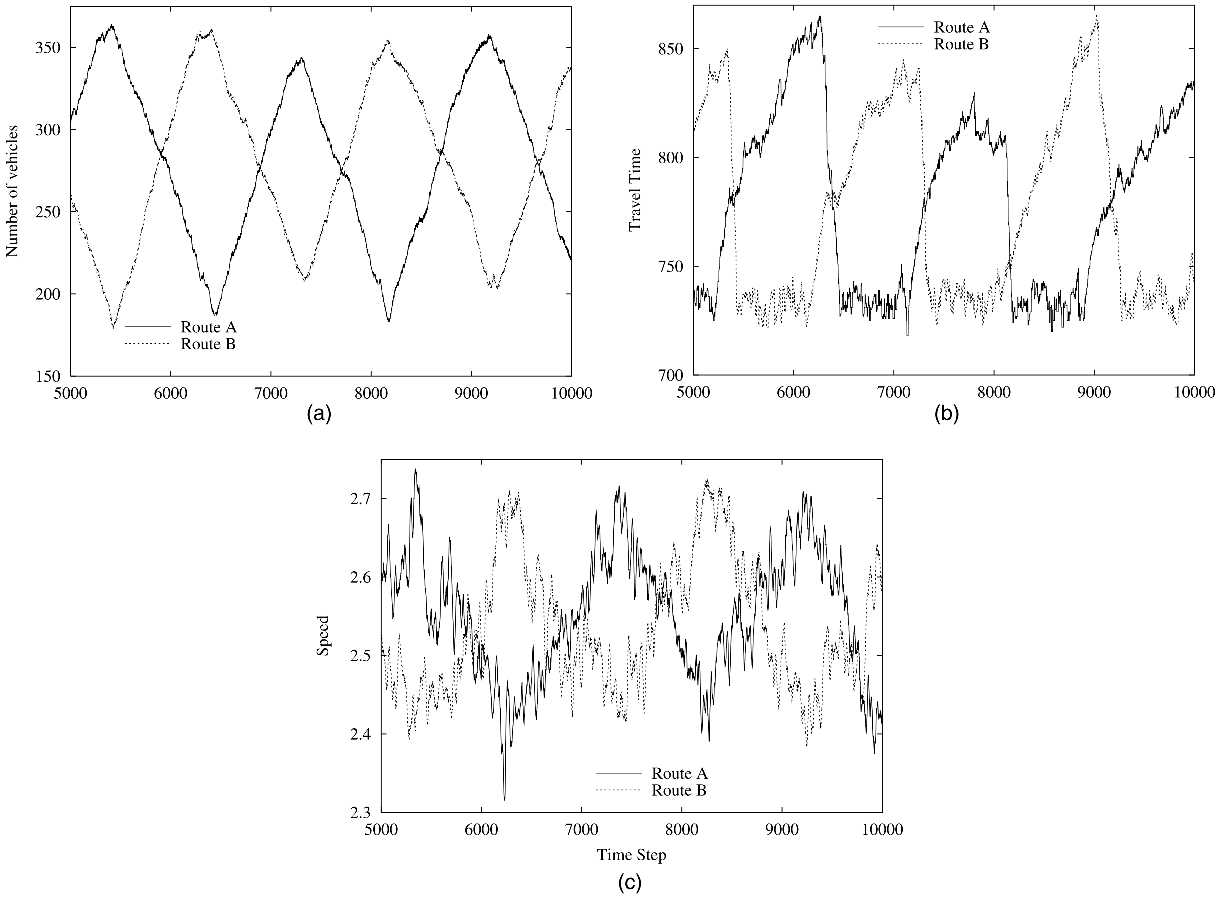

Fig. 4. (a) Number of vehicles on each route; (b) travel time on the board; (c) moving average (20 steps) of the mean speed vs. time. The parameters are $p_{\mathrm{dec}} = 0.25$, $\alpha = 1$, $L = 2000$, $p_{\mathrm{AB}} = 0.5$, $s_{\mathrm{dyn}} = 0.5$, and $s_{\mathrm{FC}} = 1$. Every quantity exhibits characteristic oscillations.

5.4.1. Parameters

There are two sets of parameters which originate either from the model used or the scenario itself. The parameters are as follows: maximum speed of vehicles ($v_{\max}$), deceleration probability (p_{dec}), input rate (α), length of the routes (L), decision of static drivers (p_{AB}), percentage of FCs (s_{FC}), and share of dynamic/equipped drivers (s_{dyn}).

Obviously, s_{dyn} and s_{FC} are interpreted as probabilities for creating a dynamic road user or a FC, respectively. With the probability p_{AB} a static driver is put on route A. The system is symmetric and thus only values $p_{\mathrm{AB}} \leqslant 0.5$ are studied. However, in most simulations the default value is $p_{\mathrm{AB}} = 0.5$, since the route length L is the only information static drivers have. Note that using $P_{\mathrm{AB}} = 0.5$ a natural equilibrium is reached, i.e., an optimal solution of the problem. In all simulations, the maximum speed is set to $v_{\max} = 3$ cells/time-step. The rate of injection is set to $\alpha = 1$, $p_{\mathrm{dec}} = 0.25$ and $s_{\mathrm{FC}} = 1$, i.e., every vehicle is a FC. For a systematic study of the influence of these parameters the reader is referred to (Wahle et al., 2000b).

5.4.2. Tools for the analysis

For our discussion on the oscillations, which appears in the next section, it is valuable to employ correlation functions. They detect and quantify coupling effects between variables. The autocorrelation for a variable ψ is defined in the following way:

$$ac_{\varphi}(\tau) = \frac{1}{\sigma(\varphi)}[\langle\varphi(t)\varphi(t+\tau)\rangle - \langle\varphi(t)\rangle\langle\varphi(t+\tau)\rangle].$$

It provides information about the temporal evolution of $\psi(\sigma(\psi)$ is the variance of $\psi)$. The travel times displayed on the board are calculated using a moving average with $N = 20$.

6. Simulation experiments

6.1. Floating-car data

In the following, FCs are used to provide dynamic data. These are inserted with the rate s_{FC} into the system. They flow with the traffic and transmit their travel time to the information board when they leave the system. The dynamic drivers who enter the system receive as information the moving average of the last 20 travel times collected.

A typical experiment is depicted in Fig. 4. The parameters are set to $p_{\mathrm{dec}} = 0.25$, $\alpha = 1$, $L = 2000$, $p_{\mathrm{AB}} = 0.5$, $s_{\mathrm{dyn}} = 0.5$; $s_{\mathrm{FC}} = 1$, i.e., every second driver processes dynamic information; and every vehicle serves as a FC. The number of vehicles, travel times, and the moving average of the velocities oscillate on both routes. Note that different from the other quantities, the fluctuations of the number of vehicles are not very big since every time-step only one vehicle can enter and two vehicles can leave the system.

The oscillations are due to the dynamic drivers who receive the information on the board. Because they behave rationally and trust the information, they aim at minimizing their own travel time. Therefore, they use the route with the shorter travel time. Since every dynamic driver behaves in the same way, the route with the smaller number of vehicles is selected more often (Fig. 4a and b). At the same time, the velocity on this route decreases and thus the travel time increases (Fig. 4c). Nevertheless, it takes some time for the FCs to transmit this to the information board since they have to reach the end of the route. During this time even more road users enter this route.

Simultaneously, the situation on the other route gets better since it is not haunted anymore by dynamic agents. The travel time on this route slowly decreases and the situation turns around. This route gets more crowded. This oscillatory behavior is well known in literature (e.g., Ben-Akiva et al., 1991; Bonsall, 1992). However, this effect seems to be intrinsic to most of the systems which provide information.

Nevertheless, the information influences the dynamics of the system in an undesirable way: it would be far more efficient to distribute the vehicles on both routes randomly. This is not only due to the effect of concentration but also to the fact that the information is too old, the drivers tend to react too late to the new situation. To quantify this behavior in more detail, the influence of the different parameters will be investigated in the following subsections.

6.2. Influence of the dynamic drivers

Since the oscillations are mainly due to the decisions of the dynamic drivers, it is interesting to study the influence of the parameter s_{dyn}, the share of dynamic drivers. Obviously, the amplitude of the oscillations depends on s_{dyn}. A dramatic situation can occur for $s_{\mathrm{dyn}} = 1$, i.e., every road user follows the information displayed on the board. In this case, it happens that one route is empty. Thus, there is no FC on it and the travel time stays the same, although the route is empty. Therefore, it is advisable to remove or slowly change information, which is too old, and set default values.

6.2.1. Correlation analysis

In order to reduce the stochastic noise in the quantities, a correlation analysis is employed, which reveals the nature of the oscillations clearer. In Fig. 5 the auto-correlation for number of cars on route A, $ac_{N_{\mathrm{A}}}(\tau)$, is depicted. For small values of s_{dyn}, the correlation is not so strong, whereas systems with a higher number of dynamic drivers s_{dyn} are strongly correlated. Similar results are found for auto-correlation of the travel time or the velocity.

6.2.2. Travel time distribution

The behavior of the two types of agents can be better understood by studying the travel time distribution. In order to provide the distribution, a histogram is used, i.e., the number of drivers in a certain interval of travel time Δt is aggregated. In our analysis, $\Delta t = 5$ time-steps. A distribution for different s_{dyn} is depicted in Fig. 6.

In a society of static agents, $s_{\mathrm{dyn}} = 0$, the agents distribute equally on both routes and the travel time distribution is more or less Gaussian, with a small standard deviation (Fig. 6a). Note that using $p_{\mathrm{AB}} < 0.5$ an optimal solution is achieved. This changes if dynamic and static drivers are

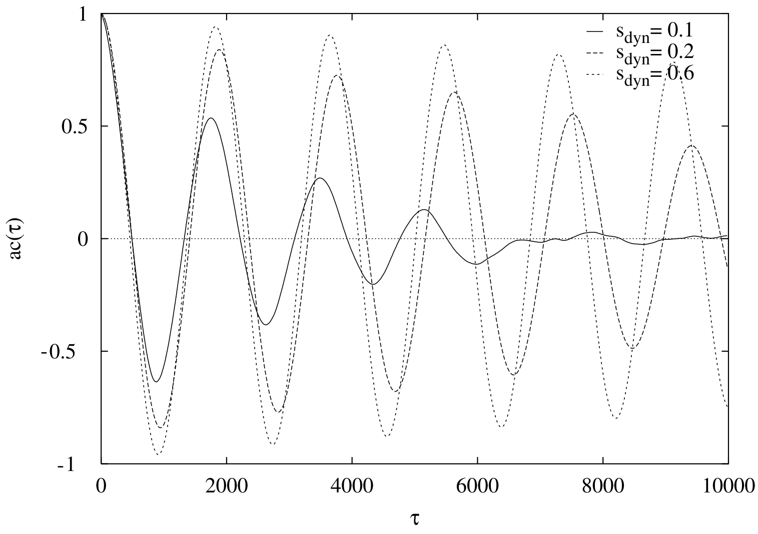

Fig. 5. Auto-correlation $ac_{N_{\mathrm{A}}}(\tau)(1)$ vs. τ, for different values of s_{dyn}. The parameters are $p_{\mathrm{dec}} = 0.25$, $\alpha = 1$, $L = 2000$, $p_{\mathrm{AB}} = 0.5$, and $s_{\mathrm{FC}} = 1$. For small values of s_{dyn} the strong correlation vanishes.

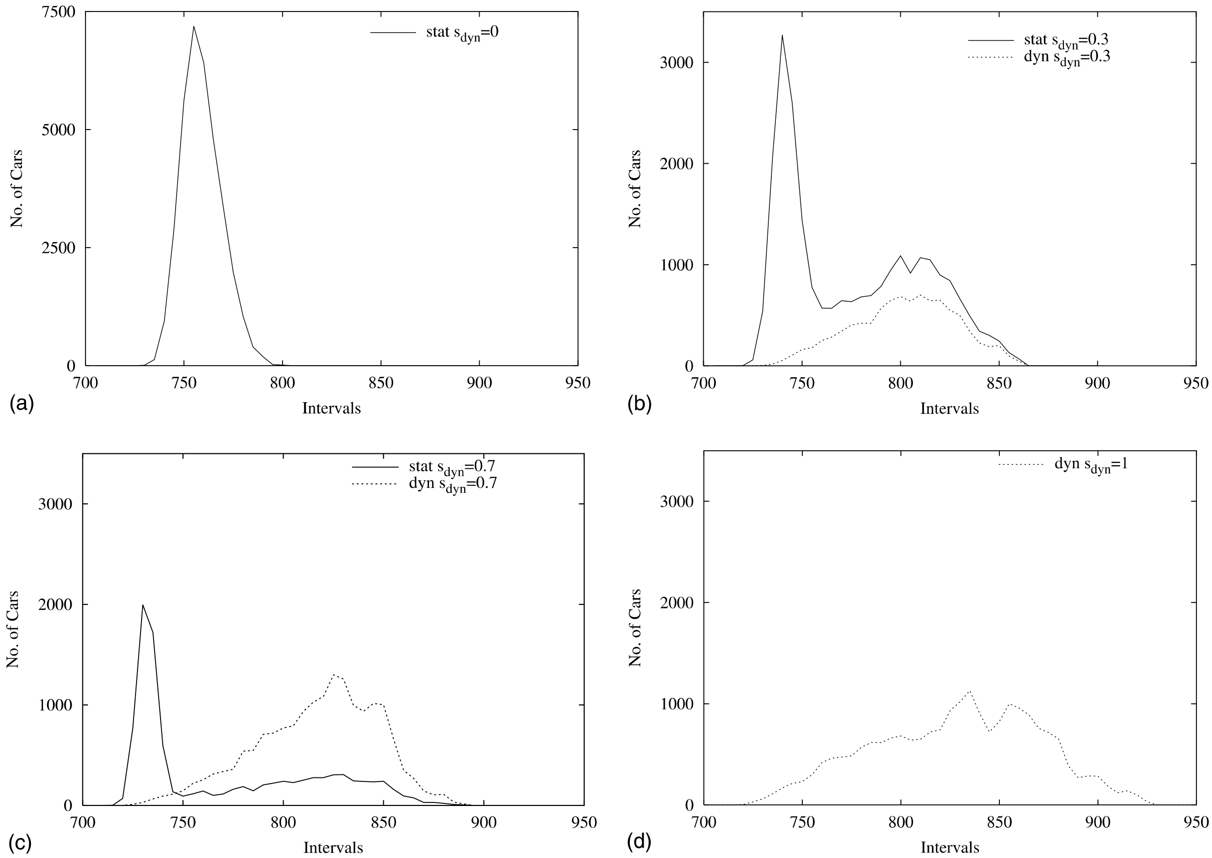

Fig. 6. Travel time distribution for static and dynamic drivers for different values of s_{dyn}. The parameters are $p_{\text{dec}} = 0.25$, $\alpha = 1$, $L = 2000$, $p_{\text{AB}} = 0.5$, and $s_{\text{FC}} = 1$. (a) If there are only static drivers they arrange in the a proper way. (b) A mixture between dynamic and static drivers is unfavorable for the dynamic ones. They introduce a second, broader peak at higher travel times. (c) This effect is amplified for higher s_{dyn}. The peak of the dynamic ones is broadened, whereas the peak for the static ones gets sharper, i.e., the minority of static drivers profit even more. (d) For a homogeneous society of dynamic drivers $s_{\text{dyn}} = 1$ the distribution is broadened further.

mixed. The dynamic drivers introduce fluctuations in the system. Their average travel time increases, whereas some static drivers profit from emptier routes. Therefore, a second peak at higher travel times emerges due to the dynamic drivers (Fig. 6b).

For higher values of s_{dyn}, this peak broadens and both peaks separate (Fig. 6c). Most of the static drivers now profit from the dynamic ones. For $s_{\text{dyn}} = 1$, every driver decides with regard to the information. A broad peak is found (Fig. 6d). However, it can be seen that the behavior of the dynamic drivers influences existing traffic patterns in an undesirable way, and leads to a sub-optimal situation, i.e., the overall flow of the system is reduced due to concentration of the equipped drivers (Fig. 9). This assumption holds even for $p_{\text{AB}} < 0.5$, i.e., if the static drivers arrange in a non-optimal way. Only for p_{AB} closed to zero, i.e., all static drivers use the same route, the dynamic agent can profit from the information (Fig. 7).

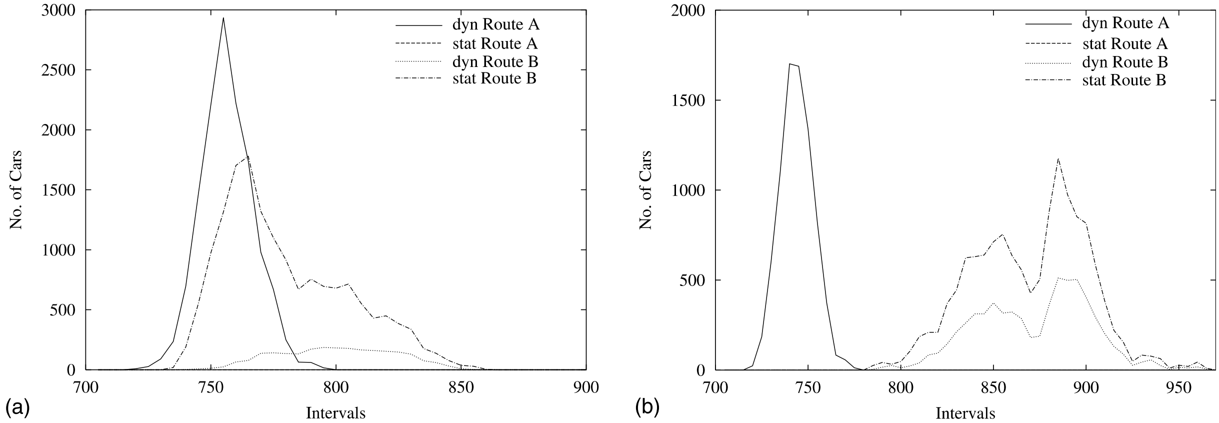

Fig. 7. Travel time distribution. Comparison of the FC-data (a) and the gradient (b). The parameters are $L = 2000$, $p_{\mathrm{dec}} = 0.25$, $\alpha = 1$, $s_{\mathrm{dyn}} = 0.5$, $s_{\mathrm{FC}} = 1$, and $p_{\mathrm{AB}} = 0$, i.e., all static drivers use route B. In this situation providing the gradient of the travel time is misleading to the dynamic drivers.

6.3. Gradient of travel time

In the previous section, it has been demonstrated that providing travel times of FCs can lead to oscillations in the system, since faster links attract more traffic and in the process are made slower (Bonsall, 1992). Therefore, another kind of information and their impact on the system is studied.

In control theory, it is well known that in order to control some quantities it is better to use the gradient of the quantity than the absolute values. Here, the moving average of the difference between two consecutive travel times of FCs $\Delta\tau_i = t_i - t_{i-1}$ is used, with t_i being the travel time of the ith FC on a route. Hence, the information displayed on the board is $\Delta\tau$, the moving average of the last twenty $\Delta\tau_i$.

6.3.1. Correlation analysis

A correlation analysis yields that using the difference of the travel times submitted as information, it is possible to reduce the fluctuations in the number of cars on both routes. But there is still some short-range correlation, which are due to the moving average used (20 time-steps). It seems that providing the trend of the travel time gives better results than the FC data itself.

6.3.2. Sub-optimal static drivers

Nevertheless, in some situations the trend can be misleading. In Fig. 7 the travel time distribution for a sub-optimal behavior, i.e., $p_{\mathrm{AB}} < 0.5$ of the static drivers is depicted. The parameters are set to $L = 2000$, $p_{\mathrm{dec}} = 0.25$, $\alpha = 1$, $s_{\mathrm{dyn}} = 0.5$, $s_{\mathrm{FC}} = 1$, and $p_{\mathrm{AB}} = 0$, i.e., all static drivers use route B. Here, the absolute travel time is the better criterion, since the bulk of the dynamic agents are on route A, and thus improve the situation for the static drivers (Fig. 7a). With the gradient as source of information a lot of dynamic agents additionally use route B and the travel times increase further (Fig. 7b). This negative effect is also reflected by the average travel time for the dynamic and static drivers. In the first scenario, $t_{\mathrm{dyn}} = 760.15$ and $t_{\mathrm{stat}} = 776.74$, whereas for the second scenario $t_{\mathrm{dyn}} = 798.05$ and $t_{\mathrm{stat}} = 866.79$. The problem with the gradient is that the absolute value of the travel time is neglected. Probably, a criterion which combines the absolute value and its gradient, will provide better results.

6.4. Global density and velocity

Up to now, information provided by FCs has been discussed. However, one main problem is that this information is delayed and sometimes too old. Better quantities to characterize the current state of the route are necessary, like the global density and the mean velocity. They are defined as follows: the density $\rho_{\mathrm{A,B}} = N_{\mathrm{A,B}}/L$, and the mean velocity $v_{\mathrm{A,B}} = \sum_{i=0}^{N_{\mathrm{A,B}}} v_{i,(\mathrm{A,B})}$. It is clear that in real systems these quantities cannot be provided, since most measurements are local.

Simulation experiments with each quantity as information on the board are carried out, and in both cases the correlation vanishes. Obviously, the difference in the experiments is that if density is the criterion, the velocity fluctuates, and vice-versa. In the case density is provided, a higher number of vehicles is injected and for the other criterion, the mean speed on both routes is quite high. In the situation, where the static drivers do behave sub-optimal, i.e., $p_{\mathrm{AB}} < 0.5$. In contrast to the previous experiments, the dynamic drivers profit from the information provided. In Fig. 8 a sub-optimal distribution of the static drivers is given, $p_{\mathrm{AB}} = 0$. All dynamic drivers use route A. This discussion shows that density and velocity are optimal criteria for the dynamic drivers.

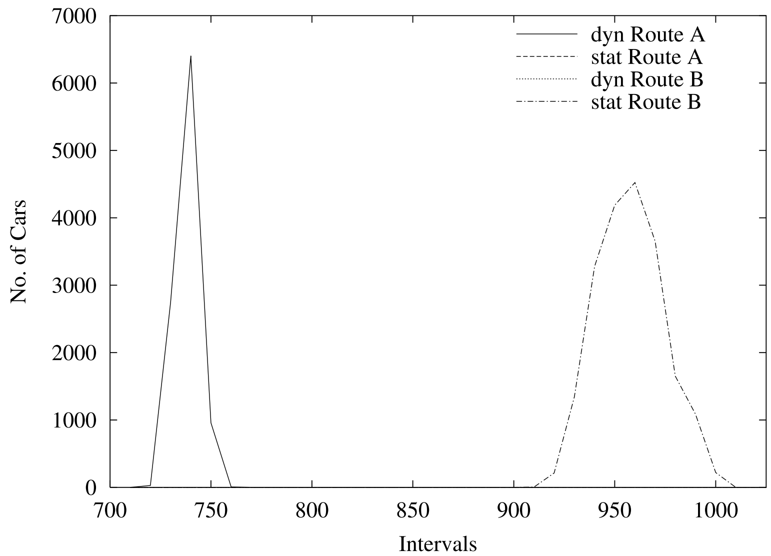

Fig. 8. Travel time distribution for giving the density. The parameters are $L = 2000$, $p_{\mathrm{dec}} = 0.25$, $\alpha = 1$, $s_{\mathrm{dyn}} = 0.5$, $s_{\mathrm{FC}} = 1$, and $p_{\mathrm{AB}} = 0$, i.e., all static drivers use route B. All dynamic drivers select route A.

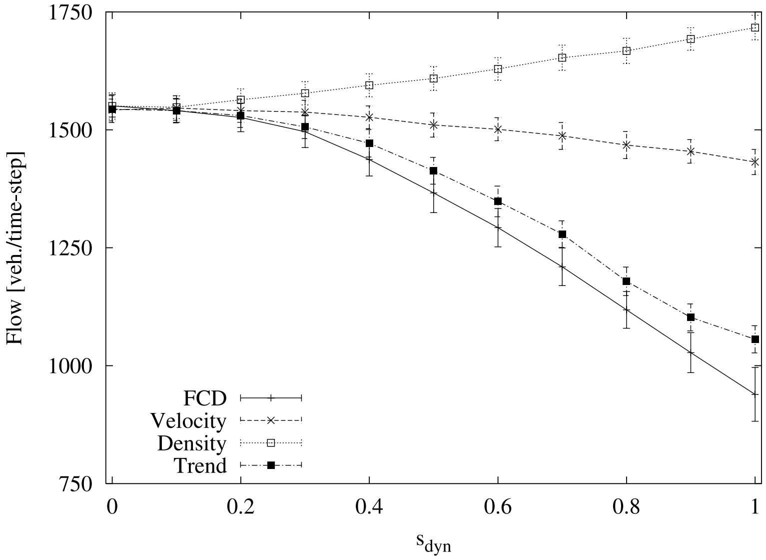

Fig. 9. Flow vs. s_{dyn} for different kinds of information. The parameters are $L = 2000$, $p_{dec} = 0.25$, $\alpha = 1$, $s_{dyn} = 0.5$, $s_{FC} = 1$, and $p_{AB} = 0.5$. For the FC data and the trend the flow goes down rapidly. This even holds for the velocity. From the traffic control point of view the density is the best criterion.

6.5. Comparison

From the traffic control point of view, an important quantity to evaluate, is the capacity or the flow, which is defined as follows: $j = N_A v_A + N_B v_B$. In Fig. 9 the different kinds of information are compared with each other. The parameters are $L = 2000$, $p_{dec} = 0.25$, $\alpha = 1$, $s_{FC} = 1$, and $p_{AB} = 0.5$, i.e., the static drivers behave optimal. It is clear that for this scenario providing the FC travel time reduces the flow with increasing s_{dyn}, since oscillations are introduced which destroy the traffic patterns. Providing the gradient of the travel time also leads to a decrease in the flow. Since the velocity criterion leads to high average velocity but reduces the density, the flow is slightly reduced, too. With regard to traffic control density is the best criterion since it helps to coordinate the agents in a sufficient way so that even the natural equilibrium of the static drivers ($p_{AB} = 0.5$) can be optimized by reducing the fluctuations.

7. Summary and conclusion

The impact of dynamic information in traffic systems is studied using a simple model of a driver as an agent in a multi-agent model and applying it to an abstract route-choice scenario. It is shown that the concentration of drivers on the recommended routes is intrinsic to many systems and leads to a negative impact on the traffic pattern, e.g., oscillations.

The behavior of the simulated entities is controlled by a two-layer architecture: the tactical and the strategic layer. The former describes the task of driving and corresponds to a microscopic traffic flow model e.g., the Nagel–Schreckenberg cellular automaton. This layer governs the behavior of the agents while they are driving on the route selected according to their strategic layer. This information assimilation and decision-making is modeled in a very abstract way using two categories: static and dynamic agents—representing conservative or flexible route selection, but it was sufficient to produce the interesting dynamics described above.

It is obvious that for the aim of studying the impact of dynamic information both agent layers are necessary. The tactical one provides a realistic driving behavior and forms the basis for higher levels of decision making that are relevant for traffic information systems based on simulations. Our study has shown that it is both, necessary and feasible to integrate models of knowledge-based behavior into traffic flow models.

By testing different types of message, we have shown that beside the amount and the validity of the information an important question is the nature of it. By its nature, travel time is not a good quantity since it introduces not only concentration but also oscillations into the system. For traffic control purposes, the best criterion is the global density since it optimizes the flow. In future, we will study the effect of providing various types of message to different drivers. This may introduce a natural diversity which avoid the effect of concentration.

In general, human factors in ITS are not well explored e.g., learning is without no doubt an important aspect that should be incorporated, too. Within the research project SURVIVE route choice experiments are performed with real road users. The results are analyzed with the methods of experimental economics. [5]

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