

Adaptive cruise control design for active congestion avoidance

Arne Kesting^{a,*}, Martin Treiber^a, Martin Schönhof^a,
and Dirk Helbing^{a,b}

^a*Technische Universität Dresden, Institute for Transport & Economics,
Andreas-Schubert-Strasse 23, D-01062 Dresden, Germany*

^b*Collegium Budapest – Institute for Advanced Study,
Szentháromság u. 2, H-1014 Budapest, Hungary*

Abstract

We present an adaptive cruise control (ACC) strategy where the acceleration characteristics, i.e., the driving style automatically adapts to different traffic situations. The three components of the concept are the ACC itself, implemented in form of a car-following model, an algorithm for the automatic real-time detection of the traffic situation based on local information, and a strategy matrix to adapt the driving characteristics, i.e., the parameters of the ACC controller to the traffic conditions. Optionally, inter-vehicle and infrastructure-to-car communication can be used to improve the accuracy for determining the traffic states. Within a microscopic simulation framework, we have simulated the complete concept on a road section with an on-ramp bottleneck, using empirical loop-detector data for an afternoon rush-hour as input for the upstream boundary. We found that the ACC vehicles improve the traffic stability and the dynamic road capacity. While the traffic congestion in the reference scenario was completely eliminated when simulating a proportion of 25% ACC vehicles, travel times were significantly reduced already for much lower penetration rates. The efficiency of the proposed driving strategy already for low market penetrations is a promising result for a successful application in future driver assistance systems.

Key words: Adaptive cruise control (ACC); Driver assistance system; Driving strategy; Traffic state detection; Microscopic traffic simulation; Car-following models

* Corresponding author. Tel.: +49 351 463 36838; fax: +49 351 463 36809
Email address: kesting@vwi.tu-dresden.de (Arne Kesting).
URL: <http://www.traffic-simulation.de> (Martin Treiber).

1 Introduction

Traffic congestion is a severe problem on freeways in many countries. In most countries, building new transport infrastructure is no longer an appropriate option. In order to decrease congestion, considerable research in the area of intelligent transport systems (ITS) is therefore performed to reach a more efficient road usage and a more ‘intelligent’ way of increasing the capacity of the road network. Examples of advanced traffic control systems are, e.g., ramp metering, adaptive speed limits, or dynamic and individual route guidance. These examples are based on a centralized traffic management, which controls the operation and the system’s response to a given traffic situation. On the other hand, automated highway systems (AHS) have been proposed as a *decentralized approach* based on automated vehicles (Varaiya, 1993). The concept of fully automated vehicle control allows for very small time gaps and platoon driving, which is a key to greater capacity. However, such systems need special infrastructure and dedicated lanes, which can only be justified if the percentage of automated vehicles is sufficiently high, which seems to make this scenario unlikely for the foreseeable future (Rao and Varaiya, 1993).

Nevertheless, partly automated driving is already commercially available for basic driving tasks such as accelerating and braking by means of adaptive cruise control (ACC). In fact, ACC systems are the first driver assistance systems with the potential to influence traffic flow characteristics. But present implementations of ACC systems are exclusively designed to increase the driving comfort, while the influence on the surrounding traffic is not yet considered or optimized. This is justified as long as the number of ACC-equipped vehicles is negligible, but the expected growing market penetration of these devices makes the question of their impact on traffic flow more pressing. Therefore, it is important to understand effects of ACC systems on the capacity and stability of traffic flow at an early stage so that their design can be adjusted before adverse traffic effects are widely manifested.

In the literature, the effects of upcoming driver assistance systems such as ACC systems on the traffic dynamics has been usually addressed by means of traffic simulation, because large-scale field experiments are hardly possible. Particularly, the microscopic modeling approach allows for a natural representation of heterogeneous traffic consisting of ACC vehicles and manually driven vehicles (Kesting et al., 2007b; Davis, 2004; VanderWerf et al., 2002; Treiber and Helbing, 2001; Marsden et al., 2001; Minderhoud, 1999). For a further overview, we refer to (VanderWerf et al., 2001). However, there is not even clarity up to now about the sign of these effects. Some investigations predict a positive effect (Treiber and Helbing, 2001; Davis, 2004), while others are more pessimistic (Kerner, 2004; Marsden et al., 2001). For realistic estimates of the impact of ACC on the capacity and traffic stability, the models

have to capture the driving dynamics of ACC and manually driven vehicles and the relevant interactions between them. Therefore, the findings depend on the model fidelity, the modeling assumptions and, mainly, on the setting for the time gap parameter, because the maximum capacity is approximately determined by the inverse of the average time gap T of the drivers (Varaiya, 1993).

In this paper, we propose an ACC-based *traffic assistance system* aiming at improving the traffic flow and road capacity and thus at decreasing traffic congestion while retaining the driving comfort. To this end, we introduce a *driving strategy layer*, which controls the settings of the driving parameters of the ACC system. While the conventional ACC *operational control layer* calculates the response to the input sensor data by means of accelerations and decelerations on a short time scale of seconds, the automated adaptation of the ACC driving parameters happens on a longer time scale of typically minutes. In order to resolve possible conflicts between the objectives of comfort and road capacity, we propose an *intelligent driving strategy that adapts the ACC driving characteristics*. For this, we consider a finite set of five ‘traffic situations’ that are associated with a specific set of ACC driving parameters. These traffic states have to be detected autonomously by each ACC-equipped vehicle. We have implemented the proposed components within a microscopic multi-lane traffic simulator in order to study the impact of the individual adaptation of each ACC-equipped vehicle on the resulting collective traffic dynamics. Thus, the simulations serve as ‘proof of concept’. Moreover, they allow for a systematic investigation of the impact of a given proportion of ACC vehicles.

The paper is structured as follows: We start with a discussion of the characteristics of manual and ACC-based driving and their representation in terms of microscopic traffic models. In Sec. 3, our concept of a *traffic assistance system* will be presented. The proposed traffic states and the traffic-state adaptive driving strategy will be introduced. In Sec. 4, the impact of the proposed ACC extension on the traffic dynamics will be investigated by means of traffic simulations of a three-lane freeway with an on-ramp bottleneck and a mixed traffic flow consisting of cars and trucks. Particularly, we focus on the collective dynamics and the travel times of various proportions of ACC-equipped vehicles. Finally, we conclude with a discussion and an outlook in Sec. 5.

2 Modeling ACC-based and human driving behavior

The recent development and availability of *adaptive cruise control* systems (ACC) extends earlier cruise control systems, which were designed to reach and maintain a certain speed preset by the driver. The ACC system extends

this functionality to situations with significant traffic where driving at constant speed is not possible. The driver can not only adjust the desired velocity but also set a certain safe time gap determining the gap to the leader when following slower vehicles (typically in the range between 0.9 s and 2.5 s). The task of the ACC system is to determine the appropriate acceleration or deceleration as a function of the traffic situation and the driver settings. In order to do so, the system is able to detect and to track the vehicle ahead, measuring the actual distance and speed difference to the vehicle ahead by means of radar or infrared sensors.

Present ACC systems offer a gain in comfort in most driving situations on freeways. Nevertheless, it should be emphasized that current ACC systems only operate above a certain velocity threshold and are limited in their acceleration range and, particularly, in their braking authority. The next generation of ACC is designed to operate in all speed ranges and in most traffic situations on freeways including stop-and-go traffic. Additionally, future ACC systems will have the potential to prevent actively a rear-end collision and, thus, to achieve also a gain in safety. However, ACC systems only control longitudinal driving. In contrast, merging, lane changing or gap-creation for other vehicles still need the intervention of the driver. So, as the driver still stays fully responsible, he or she can always override the system.

It is very useful that the input quantities of an ACC system, i.e., the vehicle's own speed, the distance to the car ahead and the velocity difference, are exactly those of many time-continuous car-following models. As the ACC response time, which is of the order of 0.1 s – 0.2 s, is generally negligible compared to the human reaction time of about 1 s (Green, 2000), suitable ACC systems specify the instantaneous acceleration $\dot{v}(t)$ of each vehicle as a continuous function of the velocity $v(t)$, the net distance (gap) $s(t)$, and the approaching rate $\Delta v(t)$ to the leading vehicle. To be an adequate candidate for simulating ACC systems, car-following models must meet some criteria: First of all, the car-following dynamics must be collision-free, at least, if this is physically possible. The dynamics should correspond to a natural and smooth manner of driving. Adaptations to new traffic situations (for example, when the predecessor brakes, or another vehicle cuts in) must be performed without any oscillations. Furthermore, the model should have only a few parameters. Each parameter should have an intuitive meaning and plausible values after calibration. Ideally, the parameter list should include the desired velocity v_0 and the desired time gap T , which are preset by the driver. By varying the remaining parameters, it should be possible to model different driving styles (such as experienced vs. inexperienced, or aggressive vs. relaxed) as well as vehicle-based limitations such as finite acceleration capabilities. Last but not least, calibration should be easy and lead to good results.

These criteria are, e.g., met by the Intelligent Driver Model (IDM) (Treiber

et al., 2000). In the following simulations, we therefore represent ACC vehicles by this model. The IDM acceleration $\dot{v}(t)$ is given by

$$\dot{v}(s, v, \Delta v) = a \left[1 - \left(\frac{v}{v_0} \right)^4 - \left(\frac{s^*(v, \Delta v)}{s} \right)^2 \right]. \quad (1)$$

This expression combines the acceleration $\dot{v}_{\text{free}}(v) = a[1 - (v/v_0)^4]$ towards a *desired velocity* v_0 on a free road with the parameter a for the *maximum acceleration* with a braking term $\dot{v}_{\text{brake}}(s, v, \Delta v) = -a(s^*/s)^2$ which is dominant if the current gap $s(t)$ to the preceding vehicle becomes smaller than the ‘effective desired minimum gap’

$$s^*(v, \Delta v) = s_0 + vT + \frac{v\Delta v}{2\sqrt{ab}}. \quad (2)$$

The *minimum distance* s_0 in congested traffic is significant for low velocities only. The dominating term of Eq. (2) in stationary traffic is vT , which corresponds to following the leading vehicle with a constant *safe time gap* T . The last term is only active in non-stationary traffic and implements an collision-free, ‘intelligent’ driving behavior including a braking strategy that, in nearly all situations, limits braking decelerations to the *comfortable deceleration* b . However, the IDM brakes stronger than b if this is required by the traffic situation. Note that all IDM parameters v_0 , T , s_0 , a and b are defined by positive values (see Table 2).

While the simple car-following approach is perfectly suited to model the dynamics of ACC-controlled vehicles, the *human* driving style differs from that in essential points such as the following:

- (1) The *finite reaction time* of humans results in a delayed response to the traffic situation.
- (2) Imperfect estimation capabilities result in *perception errors* and *limited attention spans*.
- (3) Human drivers scan the traffic situation *several vehicles ahead* while the ACC sensors are restricted to the immediate predecessor.
- (4) Furthermore, human drivers *anticipate* the future traffic situations by making use of further clues (such as brake lights) and by forming plausible hypotheses such as assuming constant accelerations of all neighboring vehicles in the next few seconds.

Despite these differences, the simple car-following approach is also able to capture many aspects of the traffic dynamics of human drivers, particularly with respect to the collective macroscopic dynamics (Treiber et al., 2000), but also on a microscopic level (Brockfeld et al., 2003). The question is why? For realistic human reaction times of the order of the time gaps, the destabilizing influences of point (1) and (2) above would lead to traffic instabilities and acci-

dents. However, points (3) and (4), i.e., the spatial and temporal anticipation, compensate for that. This has been shown using the recently proposed *human driver model* (HDM) (Treiber et al., 2006a), which extends car-following models like the IDM to the points mentioned above. It turns out that the destabilizing effects of reaction times and estimation errors are compensated for by spatial and temporal anticipation. As result, for reasonable car-following models, one obtains essentially the same longitudinal traffic dynamics, when including all four effects, compared to simulations neglecting them all.

Therefore, we may conclude that, although the mode of operation is fundamentally different, ACC-equipped vehicles and manually controlled vehicles exhibit a similar *effective* driving behavior with respect to collective properties such as the stability of traffic flow, traffic performance (measured in terms of capacity), or the emergence and propagation of congestion. Clearly, when implementing a concrete traffic assistance system according to the concept proposed in this contribution, one explicitly has to take into account the operational differences between drivers and ACC vehicles, and also the fact that non-negligible delays occur in the latter as well. As this contribution investigates the influence of ACC on macroscopic properties of traffic flow and is intended as ‘proof of concept’, it is justified to simulate the human drivers with simple car-following models such as the IDM *as well* instead of using more complex models such as the HDM. The advantage of using simple models for both human-driven and automated vehicles lies in the reduced number of parameters that need to be calibrated.

3 ACC-based traffic assistance system with an adaptive driving strategy

In this section, we generalize the ACC concept to a *traffic assistance* system, in which vehicles automatically adapt the ACC parameters to improve the traffic flow and road capacity and, thus, to decrease traffic congestion while retaining driving comfort. In order to resolve possible conflicts between the objectives of comfort and road capacity, we propose a *driving strategy that adapts the ACC driving characteristics to the local traffic situation*. For this, we consider a finite set of five traffic situations: (i) Moving in free traffic, (ii) approaching an upstream congestion front, (iii) moving in congested traffic, (iv) leaving the downstream congestion front, and (v) passing infrastructural bottleneck sections (such as road works or intersections). These traffic situations have to be detected autonomously by each ACC-equipped vehicle. Since autonomous detection alone is only possible with delays, we also consider to supplement the local information by roadside-to-car and inter-vehicle communication between the equipped vehicles (Schönhof et al., 2006; Yang and Recker, 2005; Schönhof et al., 2007).

The proposed traffic assistance system consists of several system components as displayed in Fig. 1: The main operational layer is still the ACC system calculating the acceleration $\dot{v}(t)$. The new feature of the proposed system is the strategic layer, which implements the changes in the driving style in response to the local traffic situation by changing some parameters of the ACC system. To this end, a detection algorithm determines which of the five traffic situations mentioned above applies best to the actual traffic situation. In contrast to conventional ACC systems, the driving behavior of our traffic assistance system, i.e., the acceleration, is determined in a two-step process:

- (1) The *operational level* consists in responding to changes of the ACC *input quantities* s , v , and Δv . The time scale is of the order of seconds and the spatial range is limited to the immediate predecessor.
- (2) On the *strategic level*, the traffic situation is determined locally and the driving style is adapted accordingly by changing some ACC *parameters*. The parameter settings related to the detected traffic state changes typically on time scales of minutes and in a range of typically a few hundred meters. This is analog to manual changes of the desired velocity or the time gap in conventional ACC systems by the driver, which, of course, is possible in the proposed system as well.

In the following subsections, we discuss the system components of the proposed traffic-adaptive ACC system in more detail. First, we introduce a general concept for a driving strategy that is capable of improving the traffic flow efficiency, while retaining the comfort and safety for the driver. In Sec. 3.2, we implement such a strategy in terms of a ‘driving strategy matrix’. In Sec. 3.3, we describe the detection model for determining the traffic situation based on the evaluation of the locally available data such as the vehicle’s velocity time series, its position etc. Finally, in Sec. 3.4, we discuss the extended use of non-local information sources such as inter-vehicle and infrastructure-to-car communication for an improved detection of the local traffic state.

3.1 General considerations for a comfortable and efficient driving strategy

The design of an ACC-based traffic assistance system is subject to several, partly contradictory, objectives. On the one hand, the resulting driving behavior has to be safe and comfortable to the driver. This implies comparatively large gaps and low accelerations. On the other hand, the performance of traffic flow is enhanced by lower time gaps T and larger accelerations, which can be seen when considering the main aspects of traffic performance: The *static road capacity* C defined as maximum number of vehicles per unit time and lane is strictly limited from above by the inverse of the time gap, i.e., $C < 1/T$. Moreover, simulations show that higher accelerations increase both the *traffic*

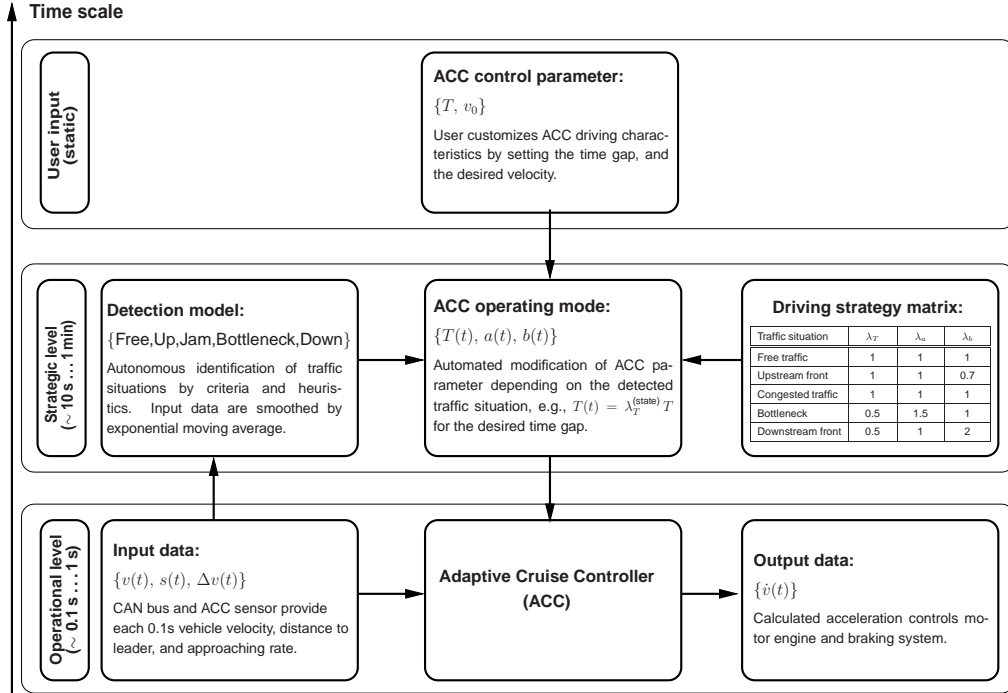


Fig. 1. Overview of the components of the proposed traffic assistance system. The *operational level* controlling the dynamics on short time scales corresponds to conventional ACC systems. The *strategic layer* containing the novel elements of our concept controls the dynamics on time scales of the order of minutes. It is coupled to the operational level via changes of the ACC model parameters T (time gap), a (desired acceleration), and b (comfortable deceleration). Additionally, the driver is able to customize the driving characteristics by setting the desired velocity v_0 and the time gap T as in conventional ACC systems. Therefore, changes of T by the strategic level are specified relative to the driver settings.

stability and the *dynamic bottleneck capacity*, i.e., the outflow from congested traffic at the bottleneck, which, typically, is lower than the free-flow capacity (Kerner and Rehborn, 1996; Cassidy and Bertini, 1999; Daganzo et al., 1999b; Kesting et al., 2007b). Our approach to solve this conflict of goals is based on the following observations:

- Most traffic breakdowns are initiated at some sort of road inhomogeneities or infrastructure-based bottlenecks such as on-ramps, off-ramps, or sections of road works (Schönhof and Helbing, 2007; Bertini et al., 2004).
- An effective measure to avoid or delay traffic breakdowns is to homogenize the traffic flow.
- Once a traffic breakdown has occurred, the further dynamics of the resulting congestion is uniquely determined by the traffic demand (which is outside the scope of this investigation), and by the traffic flow in the immediate neighborhood of the downstream congestion front (Daganzo et al., 1999a). In many cases, the downstream front is fixed and located near a bottleneck, as found in empirical investigations (Schönhof and Helbing, 2007).

- Traffic safety is increased by reducing the spatial velocity gradient at the upstream front of traffic congestion, i.e., by reducing the risk of rear-end collisions.

In the context of the ACC-based traffic assistance system, we make use of these observations by *only temporarily changing the comfortable settings of the ACC system in specific traffic situations*. The situations in which this is necessary have to be determined autonomously by the equipped vehicle and it has to take specific actions to improve the traffic performance. To this end, we propose the following discrete set of five traffic states and the corresponding actions:

- (1) **Free traffic.** This is the default situation. The ACC settings are determined solely by the maximum individual driving comfort. Since each driver can set his or her own parameters for the time gap and the desired velocity, this may lead to different settings of the ACC systems.
- (2) **Upstream jam front.** Here, the objective is to increase safety by reducing velocity gradients. Compared to the default situation, this implies earlier braking when approaching slow vehicles. Note that the operational layer always assures a safe approaching process independently from the detected traffic state.
- (3) **Congested traffic.** Since drivers cannot influence the development of traffic congestion in the bulk of a traffic jam, the ACC settings are reverted to their default values.
- (4) **Downstream jam front.** To increase the dynamic bottleneck capacity, accelerations are increased and time gaps are temporarily decreased.
- (5) **Bottleneck sections.** Here, the objective is to locally increase the capacity, i.e., to *dynamically ‘fill’ the capacity gap*. This requires a temporary reduction of the time gap.

Note that the drivers typically experience the sequence of these 5 traffic states when travelling through congested traffic. We emphasize that the total fraction of time periods during which the ACC settings deviate from the default state is usually only a few percent. Moreover, we show in Sec. 4 that even a small percentage of equipped vehicles driving according to the above ACC strategy substantially decreases the size and duration of congestion and thus the travel time. This means, despite a temporary deviation from the most comfortable ACC settings, the drivers of such systems will profit considerably overall.

3.2 Implementation of the ACC traffic assistance: Driving strategy matrix

In this section, we implement the above concept for an ACC system based on the Intelligent Driver Model (IDM) (Treiber et al., 2000) as discussed in Sec. 2.

Three of five IDM parameters listed in Table 2 below directly correspond to the different aspects of the adaptation strategy: The *acceleration parameter* a gives an upper limit for the acceleration $\dot{v}(t)$ of the ACC-controlled vehicle. Consequently, this parameter is increased when leaving congestion, i.e., when the state ‘downstream front’ has been detected. The *comfortable deceleration* b characterizes the deceleration when approaching slower or standing vehicles. Obviously, in order to be able to brake with lower decelerations, one has to initiate the braking maneuver earlier. Since this smoothes upstream fronts of congestion, the parameter b is decreased when the state ‘upstream front’ has been detected. Notice that, irrespective of the value of b , the ACC vehicle brakes stronger than b if this is necessary to avoid collisions. Finally, the *time gap parameter* T is decreased if one of the states ‘bottleneck’ or ‘downstream front’ is detected.

In order to be acceptable for the drivers, the system parameters need to be changed in a way that preserves the individual settings and preferences of the different drivers and also the driving characteristics of different vehicle categories such as cars and trucks. Particularly, the preferred time gap T can be changed both by the driver, and by the event-oriented automatic adaptation (cf. Fig. 1). This can be fulfilled by formulating the changes in terms of *multiplication factors* λ_a , λ_b , and λ_T defined by the relation

$$a^{(s)} = \lambda_a^{(s)} a, \quad b^{(s)} = \lambda_b^{(s)} b, \quad T^{(s)} = \lambda_T^{(s)} T, \quad (3)$$

where the superscript (s) denotes one of the five traffic states, to which the respective value applies. Furthermore, a , b , and T denote the default values of the IDM parameters as given in Table 2 below. In summary, this implementation can be formulated in terms of a *strategy matrix* as depicted in Table 1. Of course, all changes are subject to restrictions by legislation (e.g., the lower limit for T), or by the vehicle type such as an upper limit for a , particularly for trucks.

3.3 Detection algorithm for a vehicle-based identification of traffic states

Let us now present a detection model for an automated, vehicle-based identification of the local traffic situation as required for the proposed driving strategy matrix. Our detection model is based on locally available time series data. The Controller Area Network (CAN) of the vehicle itself provides the vehicle’s own speed, whereas the velocity of the leader is measured by the radar sensor of the ACC system. Both velocities can be used in a weighted average, but for the sake of simplicity we only focus on the vehicle’s own velocity. Due to short term fluctuations, the time series data require a smoothing in time in order to reduce the level of variations. In our traffic simulator (cf. Sec. 4 below), we have used an exponential moving average (EMA) for a measured

Table 1

The *driving strategy matrix* summarizes the implementation of the ACC driving strategy. Each of the traffic situations corresponds to a different set of ACC control parameters. We represent the ACC driving characteristics by the *time gap* T , the *maximum acceleration* a , and the *comfortable deceleration* b , which are model parameters of the Intelligent Driver Model (IDM). λ_T , λ_a , and λ_b are the multiplication factors in relation (3). For example, $\lambda_T = 0.5$ denotes a reduction of the default time gap T by 50% in bottleneck situations.

Traffic situation	λ_T	λ_a	λ_b	Driving behavior
Free traffic	1	1	1	Default/Comfort
Upstream front	1	1	0.7	Increased safety
Congested traffic	1	1	1	Default/Comfort
Bottleneck	0.5	1.5	1	Breakdown prevention
Downstream front	0.5	2	1	High dynamic capacity

quantity $x(t)$,

$$x_{\text{EMA}}(t) = \frac{1}{\tau} \int_{-\infty}^t dt' e^{-(t-t')/\tau} x(t'), \quad (4)$$

with a relaxation time of $\tau = 5$ s. As the initial conditions only affect the first few 100m in the simulations, they are irrelevant for sufficiently large vehicle positions. The EMA allows for an efficient real-time update by solving the corresponding ordinary differential equation

$$\frac{d}{dt} x_{\text{EMA}} = \frac{x(t) - x_{\text{EMA}}(t)}{\tau}. \quad (5)$$

For an identification of the proposed five traffic states we define the following criteria: The *free traffic state* is characterized by a high average velocity, i.e.,

$$v_{\text{EMA}}(t) > v_{\text{free}}, \quad (6)$$

where $v_{\text{free}} = 60$ km/h is a typical threshold value. In contrast, the *congested traffic state* is characterized by a low average velocity, namely

$$v_{\text{EMA}}(t) < v_{\text{cong}}, \quad (7)$$

with a threshold of $v_{\text{cong}} = 40$ km/h. The detection of an upstream or downstream jam front relies on a *change* in speed compared to the exponentially averaged past of the speed. Approaching an *upstream jam front* is therefore characterized by

$$v(t) - v_{\text{EMA}}(t) < -\Delta v_{\text{up}}, \quad (8)$$

whereas a *downstream front* is identified by an acceleration period, i.e.,

$$v(t) - v_{\text{EMA}}(t) > \Delta v_{\text{down}}. \quad (9)$$

Both thresholds are of the order of $\Delta v_{\text{up}} = \Delta v_{\text{down}} = 10 \text{ km/h}$.

The most important adaptation of the driving style is related to the *bottleneck state*. The identification of this state requires information about the infrastructure, because bottlenecks are typically associated with spatial modifications in the freeway design such as on-ramps, off-ramps, lane closures, gradients or construction sites. We assume that this information is provided by a digital map database containing the position of a bottleneck ($x_{\text{begin}}, x_{\text{end}}$) in combination with a positioning device (GPS receiver), which provides the actual vehicle position $x(t)$ (Drane and Rizos, 1998). This information allows for an identification of the bottleneck state by the spatial criteria

$$x(t) > x_{\text{begin}} \quad \text{AND} \quad x(t) < x_{\text{end}}. \quad (10)$$

The proposed criteria offer the possibility that no criterion is fulfilled or, vice versa, multiple criteria are met simultaneously. To this end, we need a *heuristics* for the discrete choice problem. From our visualized traffic simulations (cf. Fig. 2), we found that the following priority order is the most adequate one: *downstream front* \rightarrow *bottleneck* \rightarrow *traffic jam* \rightarrow *upstream front* \rightarrow *free traffic* \rightarrow *no change*. Thus, a detected ‘downstream front’ has a higher priority than a ‘bottleneck’ state etc. Note that this decision order also reflects the relevance of the driving strategy associated with these traffic states for an efficient traffic flow. A more sophisticated heuristics would consist in a dynamic adaptation of the thresholds used in the criteria of Eqs. (6) – (9).

3.4 Inclusion of inter-vehicle and infrastructure-to-car communication

So far, the detection model is exclusively based on *local information* that is provided autonomously by the vehicle’s own velocity time series, the ACC sensor data, and a GPS positioning device. Let us shortly discuss the principal limitations of this approach. An autonomous detection in real-time has to struggle with a time delay due to the exponential moving average, that is of the order of τ . This fact limits the response time of the traffic state identification algorithm. Particularly, the adaptation towards a smooth deceleration behavior when approaching a dynamically propagating upstream front requires the knowledge of the jam front position at an early stage in order to be able to switch to the new driving strategy in time. For a more advanced vehicle-based traffic state estimation, non-local information can be additionally incorporated in order to improve the detection speed and quality. For example, a short-range inter-vehicle communication (IVC) (Yang and

Recker, 2005; Schönhof et al., 2006; Schönhof et al., 2007) is a reasonable extension providing up-to-date information about *dynamic* up- and downstream fronts of congested traffic, which cannot be estimated without delay by local measurements only. Furthermore, in case of a *temporary bottleneck* such as a construction site or accident that is not listed in the digital map database, the information about the location could be provided by communication with a stationary sender upstream of the bottleneck (infrastructure-to-car communication). Notice that we do not use IVC for a direct *control* of ACC. We merely incorporate additional, non-local information sources for an improved traffic-state estimation.

4 Multi-lane freeway simulation with an on-ramp bottleneck

Let us now evaluate the impact of the proposed ACC-based traffic assistance system by means of traffic simulations. The microscopic modeling approach allows for a detailed specification of the parameters and proportions of cars and trucks, as well as the proportions of ACC and manually controlled vehicles. As introduced in Sec. 2, we use the Intelligent Driver Model (IDM) with the parameter sets for cars and trucks given in Table 2 consistent with real traffic data (Treiber et al., 2000). The vehicle length has been set to 4 m for cars and 12 m for trucks. Furthermore, lane-changing is a required ingredient for realistic simulations of freeway traffic and merging zones such as the considered on-ramp. We have modeled lane-changing decisions by the MOBIL (‘Minimizing Overall Braking Induced by Lane Changes’) algorithm proposed by Kesting et al. (2007a). The basic idea of MOBIL is to measure both the attractiveness of a given lane, i.e., its utility, and the risk associated with lane changes in terms of accelerations as calculated with the underlying car-following model, i.e., with the IDM. While a safety criterion prevents critical lane changes and collisions, an incentive criterion evaluates the prospective (dis-)advantage in the new lane. Notice that the ACC system only controls longitudinal driving. For this reason, we use the same lane-changing parameters for ACC vehicles.

In the simulation runs, a given proportion of vehicles is equipped with ACC systems (cf. Fig. 2). Each ACC vehicle determines the local traffic situation autonomously by evaluating the locally available data. Depending on the detected traffic state, the individual ACC parameters T , a , and b are immediately changed by the multipliers of the driving strategy matrix listed in Table 1. The automatic adaptation of the driving style induces a reaction to the traffic dynamics of the overall system. In the following subsections, we evaluate the impact of the proportion of ACC vehicles, the driving strategies, and the boundary conditions on the capacity and stability of traffic flow by means of numerical simulations. For a direct evaluation of the effects of the proposed adaptive driving strategy of ACC vehicles, we use the same default param-

Table 2

Model parameters of the Intelligent Driver Model (IDM) for cars and trucks as used in the simulations. The parameters of the ‘driving strategy matrix’ are summarized in Table 1. The website <http://www.traffic-simulation.de> provides an interactive simulation and documentation of the IDM in combination with the lane-changing model MOBIL.

Model Parameter	Car	Truck
Desired velocity v_0	120 km/h	85 km/h
Safe time gap T	1.5 s	2.0 s
Maximum acceleration a	1.4 m/s ²	0.7 m/s ²
Desired deceleration b	2.0 m/s ²	2.0 m/s ²
Jam distance s_0	2 m	2 m

eters for human drivers and ACC-equipped vehicles assuming that the ACC parameters in the default state are adjusted to the natural driving style.

4.1 Spatiotemporal dynamics for various ACC proportions

We have investigated a traffic scenario with open boundary conditions and an on-ramp as typical representative for a stationary bottleneck. The simulated three-lane freeway section is 13 km long. The center of the on-ramp merging zone of length $L_{\text{rmp}} = 250$ m is located at $x = 10$ km. As upstream boundary condition, we have used empirical detector data from the German freeway A8 from Munich to Salzburg. Figure 3 shows the 1-min data of the lane-averaged traffic flow and the proportion of trucks during the evening rush-hour between 15:30h and 20:00h. Although we also used the average velocities provided by the detectors, they turned out to be irrelevant for the traffic dynamics because the vehicles relax their velocities in the first few 100 m according to the local traffic situation. Notice that, in the real-world data, traffic further downstream of the detector was congested between 17:00h and 19:30h due to an on-ramp and an uphill gradient, cf. Fig. 14 in Treiber et al. (2000). Moreover, we have assumed a constant ramp flow of 750 vehicles/h with 10% trucks. The parameters in Table 2 are calibrated in order to reproduce the empirical traffic breakdown further downstream at a bottleneck. For details, we refer to Treiber et al. (2000).

For an investigation of the impact of the proposed traffic assistance system on the traffic dynamics, we have carried out several simulations with varying proportion of vehicles equipped with ACC systems. The resulting spatiotemporal dynamics for ACC penetrations of 0%, 5%, 15% and 25% are shown in Fig. 4. For the purpose of better illustration, we have plotted the lane-averaged mean



Fig. 2. Screenshot of our traffic simulator, showing the on-ramp scenario studied in Sec. 4.1. In our visualization, the current traffic state of each ACC vehicle is displayed by a changing vehicle color allowing for a direct, visual assessment of the detected states. In contrast, non-ACC vehicles are displayed in grey color. The parameters of the strategy matrix can be changed interactively by the researcher in order to test new strategy matrices directly. For matters of illustration, two simulation runs are displayed. In the upper simulation, 100% of the vehicles are equipped with the ACC-based traffic assistance system. The different vehicle colors indicate the locally detected traffic states. The reference case without ACC equipment (grey vehicle color) displayed in the lower simulation window shows congested traffic at the bottleneck. In both simulations, the same time-dependent upstream boundary conditions have been used (cf. Fig. 3).

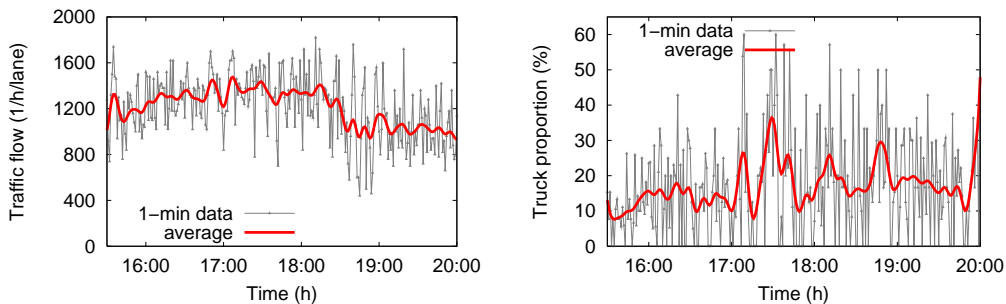


Fig. 3. Time series of empirical 1-min loop detector data of the lane-averaged traffic flow and truck proportion used as upstream boundary conditions in our traffic simulations. The data show the afternoon rush-hour peak of the German autobahn A8 from Munich to Salzburg. The moving average values (thick lines) are only plotted for a better overview over the strongly fluctuating quantities.

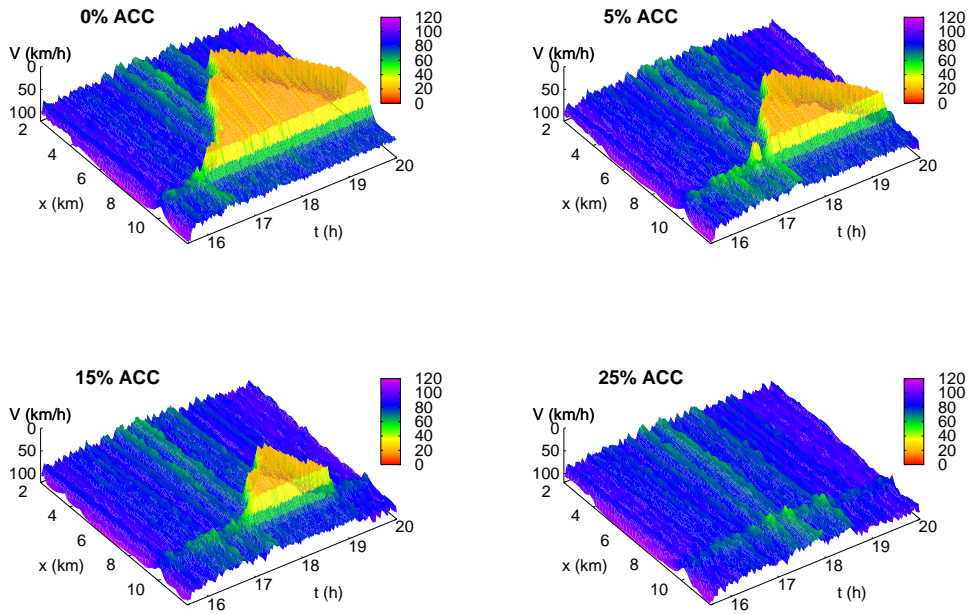


Fig. 4. Spatiotemporal traffic dynamics around an on-ramp located at $x = 10$ km for different proportions of ACC vehicles, represented by the lane-averaged velocity of a three-lane freeway upside down. The inflow at the upstream boundary is taken from empirical 1-min detector data shown in Fig. 3 during the evening rush-hour. The simulations show the positive impact of the *traffic assistance system* for ACC-equipped vehicles introduced in Sec. 3.

velocity upside down. Thus, a decrease in the speed due to an increase of the inflow as well as congested traffic are clearly displayed.

The simulation scenario without ACC vehicles shows a traffic breakdown at $t \approx 17:00$ h at the on-ramp due to the increasing incoming traffic at the upstream boundary during the rush-hour. The other three diagrams of Fig. 4 show simulation results for an increasing proportion of ACC-equipped vehicles, which reduces traffic congestion significantly. Already a proportion of 5% ACC vehicles improves the traffic flow. This demonstrates the efficiency of the proposed automated driving strategy and its positive effect on capacity already for small penetration levels. An equipment level of 25% ACC vehicles avoids the traffic breakdown in this scenario completely.

4.2 Influence on capacity

Let us study the traffic dynamics in more detail by investigating flow-density data. To facilitate a direct comparison with the data collected from double-loop detectors, we have applied the same data aggregation technique by intro-

ducing ‘virtual detectors’ mimicking real-world cross-section measurements. We have recorded the traffic flow Q and the mean velocity V within 1-min sampling intervals. Furthermore, we have determined the density ρ via the hydrodynamic relation $Q = \rho V$. All quantities are averaged over the three lanes of the simulated road section. Figure 5 shows the resulting flow-density relations of the simulations for several cross-sections located up- and downstream of the on-ramp bottleneck. For direct comparison, we have displayed the data of the simulations of Fig. 4 with an ACC proportion of 25% and without ACC vehicles in the same plots.

Upstream of the bottleneck (diagrams (a) and (b) of Fig. 5), the flow-density data show the branch of free traffic flow $Q \approx v_0 \rho$, for $\rho < 30$ veh./km/lane, and the widely scattered area of congested traffic for $\rho > 30$ veh./km/lane. After the traffic breakdown, the flow is reduced by approximately 10–20% compared to the maximum value of Q in the branch belonging of the free traffic. The data of the detectors located downstream of the on-ramp demonstrate that the maximum flow in free traffic has been increased in the simulation scenario with 25% ACC vehicles. In some sense, the local reduction of the time gap by a small proportion of ACC vehicles is able to ‘fill’ the capacity gap at the bottleneck, at least partially. Therefore, the performance loss due to the *capacity drop* (Kerner and Rehborn, 1996; Cassidy and Bertini, 1999; Daganzo et al., 1999b; Kesting et al., 2007b) in congested traffic is avoided (or delayed for smaller ACC proportions). The approach of jam-avoiding driving by ACC vehicles, which dynamically increases the local capacity near the on-ramp, can be transferred to other kinds of bottlenecks as well (Kesting et al., 2006).

4.3 Evaluation of the instantaneous and cumulated travel time

Let us now consider the travel time as the most important variable of an user-oriented measure of the quality of service (Hall et al., 2000). While the *instantaneous travel time* as a function of the simulation time reflects mainly the perspective of the drivers, the *cumulated travel time* is a performance measure of the overall system that can be associated with the economic costs of traffic jams. We define the instantaneous travel time of a road segment $[x_{\text{start}}, x_{\text{end}}]$ by

$$\tau_{\text{inst}}(t) = \int_{x_{\text{start}}}^{x_{\text{end}}} \frac{dx}{V(x, t)}. \quad (11)$$

In a microscopic simulation, the average velocity $V(x, t)$ can be approximated from the velocities v_i and the integral by the sum over the gaps $\Delta x_i = x_{i-1} - x_i$ of all vehicles i according to

$$\tau_{\text{inst}}(t) = \sum_i \frac{\Delta x_i(t)}{v_i(t)}. \quad (12)$$

Moreover, the cumulated travel time is simply the vehicle number on the simulated section integrated over time.

Figure 6 shows the instantaneous and cumulated travel times for the simulation runs in Fig. 4. Obviously, the breakdown of the traffic flow has a strong effect on the travel time. For example, the cumulated travel time without

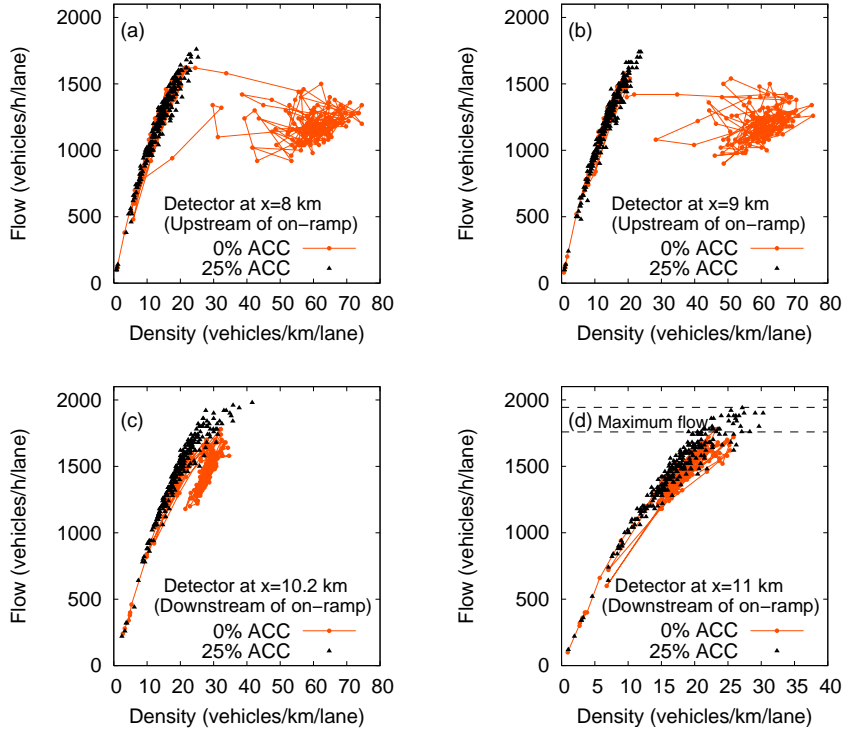


Fig. 5. Flow-density relations of 1-min data for four cross sections up- and downstream of an on-ramp located at $x = 10$ km. Results of the simulations without ACC vehicles are directly compared with results of an ACC equipment level of 25%. Due to the locally increased capacity by the ACC driving strategy, it can practically avoid a traffic breakdown.

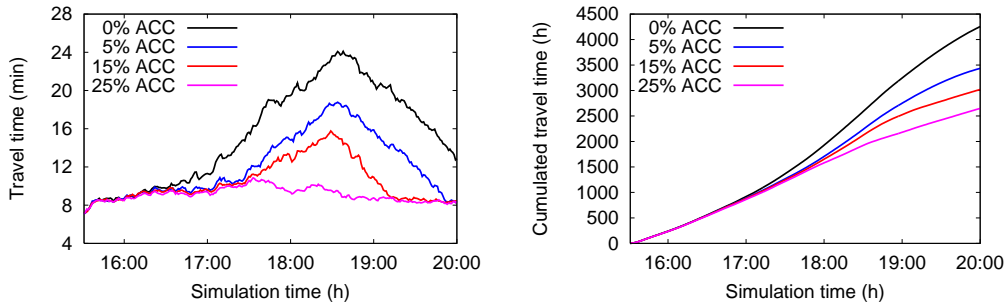


Fig. 6. Instantaneous and cumulated travel times for different ACC equipment levels. The left diagram demonstrates the strong effect of a traffic breakdown on the resulting travel times, while the cumulated travel time indicates the impact of congestion on the overall system.

ACC vehicles amounts to about 4000 h, whereas the scenario with a fraction of 25% ACC vehicles results only in approximately 2500 h. Therefore, the traffic breakdown leads to an increase of the overall travel time by 60% compared to free flow conditions. In comparison, the travel time of individual drivers at the peak of congestion ($t \approx 18:45$ h) is even tripled compared to the situation without congestion. The time series of the instantaneous travel times indicate that an increased ACC proportion delays the traffic breakdown. Already for 5% ACC vehicles, the traffic breakdown is shifted by 20 min compared to the traffic breakdown at $t \approx 17:00$ h in the scenario without ACC vehicles.

The results in Fig. 6 demonstrate that both the instantaneous and the cumulated travel time are sensitive measures for the impact of traffic congestion and, thus, the quality of service. In contrast to other macroscopic quantities such as traffic flow or average velocity, the travel time sums up over *all vehicles* in the simulation and weights their influence directly in terms of the travel time. As shown in our simulations, already a slightly increased capacity due to the adaptive driving strategy of a small fraction of traffic-assisted vehicles can have a significant positive impact on system performance.

4.4 Dependence on the penetration rate of ACC vehicles

Finally, we have systematically studied the robustness of the presented simulation results and their dependence on the percentage of ACC vehicles. For sensitive performance measures such as travel times, the time of the traffic breakdown is important, which, in the simulation of a multi-lane freeway with an on-ramp bottleneck and several vehicle types, is a stochastic variable. Consequently, the travel time is a stochastic variable as well. We have performed 51 simulation runs varying the ACC proportion between 0% and 50% for each of the four simulation scenarios depicted in Fig. 7. The resulting cumulated travel times for each simulation run are shown as triangles in the diagrams of Fig. 7. Additionally, we have calculated the average travel time and its variation by a Gaussian-weighted linear regression with a smoothing width of $\sigma = 0.05$ with respect to the proportion of ACC vehicles. The diagrams referring to different simulation settings show a similar behavior: The cumulated travel times decrease monotonously when increasing the fraction of ACC vehicles until the travel time for free traffic is reached for an ACC percentage of about 25%. Remarkably, the cumulated travel time already decreases significantly for low equipment levels of only a few percent of vehicles. This opens good perspectives for an introduction of this traffic assistance system into the market.

The simulation results shown in Fig. 7(a) refer to the simulation scenario already discussed before (cf. Figs. 4 and 6). In the simulations shown in the

diagram 7(c), we have varied the reduction factor of the time gap, which is the most important parameter for the bottleneck strength from $\lambda_T^{\text{bottleneck}} = 0.5$ to $\lambda_T^{\text{bottleneck}} = 0.7$. The diagram shows a similar monotonous relationship between the proportion of ACC and the travel time. As expected, the decrease of the cumulated travel time is shifted towards higher ACC equipment rates compared to the simulations with $\lambda_T^{\text{bottleneck}} = 0.5$, given the same empirical boundary conditions.

We also investigated the effects of distributed driving parameters for ACC and not equipped vehicles in order to represent individual differences in the driving behavior. In Fig. 7(b) and 7(d), we show simulations with uniformly distributed time gaps T and desired velocities v_0 of driver-vehicle units. The averages of the parameter values have been left unchanged and the width of the distributions have been set to 25% of T and v_0 , respectively, i.e., the individual values vary between 75% and 125% of the average parameter value. Again, we have obtained a similar reduction of traffic congestion with an increasing ACC proportion, which demonstrates the robustness of the proposed adaptive driving strategy. The higher total travel times compared to simulations without statistically distributed parameters can be explained by the fraction of vehicles driving with a lower desired velocity v_0 or a larger time gap T . Note that, for dense traffic conditions, these vehicles also determine the overall driving behavior of driver-vehicle units with higher desired velocities.

5 Discussion and outlook

Adaptive cruise control (ACC) systems are already available on the market. They will spread in the future, and the next generation of ACC systems is expected to extend their range of applicability to low speeds and ‘follow to stop’ capability. This offers a realistic perspective for a decentralized traffic optimization strategy based on ACC-equipped vehicles. Up to now, ACC systems were mainly optimized for the user’s driving comfort and safety. In order to ensure that ACC systems are implemented in ways that improve, rather than degrade traffic conditions, we have proposed an ACC-based *traffic assistance system* with an active jam-avoidance strategy. The main innovation of our concept is that ACC vehicles implement variable driving strategies and choose a specific driving strategy according to the actual traffic situation. Based on local information, each vehicle detects autonomously the traffic state and automatically adapts the parameters, i.e., the driving style, of the ACC system. The detection algorithm can be improved by non-local information provided by infrastructure-to-car and inter-vehicle communication, which offers an interesting application field for wireless communication technologies (Schönhof et al., 2006).

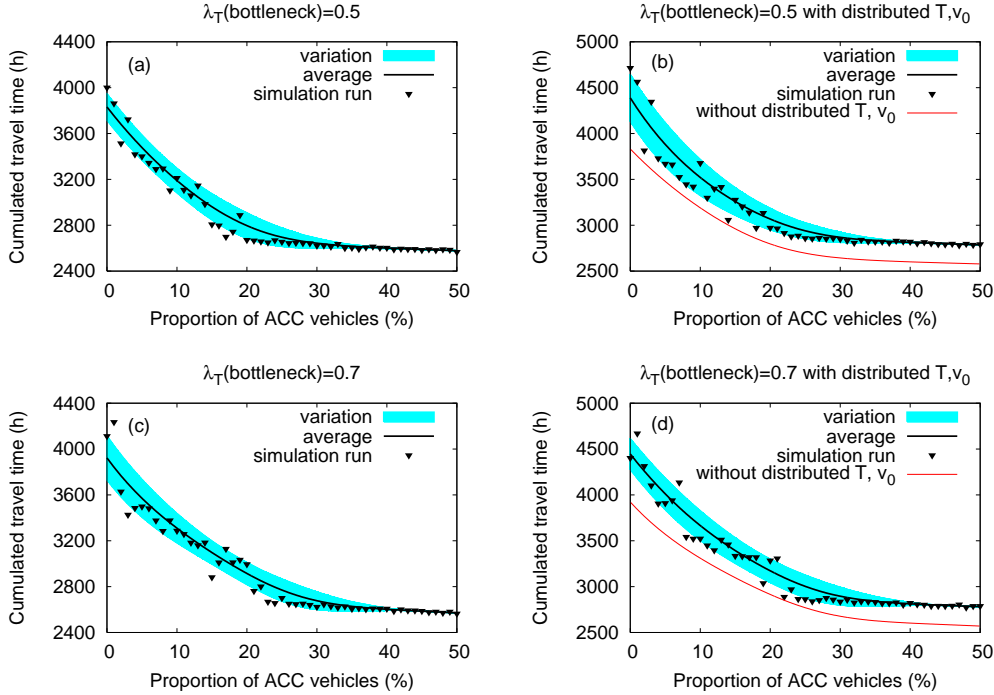


Fig. 7. Cumulated travel time as a function of the proportion of ACC vehicles for different simulation settings (cf. main text). Each data point represents a single simulation run. The average value and its variation are calculated by a Gaussian-weighted linear regression method. All simulated systems show a similar monotonous reduction until the value corresponding to free traffic is reached. The reduction is significant already for low equipment rates.

We have presented a concrete model specification of the traffic assistance system and implemented the components within a microscopic simulation framework. The simulations served as ‘proof of concept’ of our *driving strategy matrix*, which is based on a finite set of 5 traffic states in order to resolve conflicting objectives between driving comfort and road capacity. The simulations of a freeway section with an on-ramp showed that reducing the time gap locally in the ‘bottleneck state’ and at the ‘downstream front’ of congested traffic is sufficient to reach efficient traffic flow, while most of the time our proposed ACC system is driving with natural parameter settings. As a bottleneck is *defined* by a capacity reduction, the *reduction of the time gap at a bottleneck manages to fill the capacity gap*. This approach is also applicable to other kinds of bottlenecks such as an uphill gradient (Kesting et al., 2006).

Furthermore, our simulations of the afternoon rush-hour peak of a German autobahn rush-hour showed that already a small percentage of ‘intelligent’ ACC vehicles, i.e., a relatively modest change in the maximum free flow can significantly improve the traffic performance. This can delay the breakdown of traffic flow and increase the dynamic capacity, which leads to reduced queue lengths in congested traffic. The simulations demonstrate that already an ACC

equipment level of 5% improves the traffic flow quality and reduces the travel times for the drivers in a relevant way. A systematic increase of the ACC penetration level for different simulation settings and statistically distributed model parameters achieves a monotonous decrease of the cumulated travel time. The presented results are largely independent of details of the model, the upstream boundary conditions, or the type of road inhomogeneity. Note that this is crucial for a successful introduction of the traffic assistant system into the market.

The simulations were based on the assumption that only a small fraction of ACC vehicles adapts their parameters according to the proposed *jam-avoiding* driving strategy, while the manually controlled vehicles applied a time-independent, constant driving style. The presented findings demonstrate the impact of the individual driver behavior on the overall traffic dynamics. This is also relevant for manual driving because human drivers generally respond to the local traffic conditions as well (Treiber et al., 2006b). For example, subconscious adaptation processes *decrease* the local capacity which has been interpreted as ‘frustration effect’ (Treiber and Helbing, 2003). A higher impact on the efficiency of the traffic flow would even be reached if human drivers act according to the proposed jam-avoiding driving strategy as well. Consequently, it would be desirable to teach driver behaviors that are beneficial to the overall system (such as attentive driving at bottlenecks and prompt acceleration when leaving a jam) in driving lessons, next to established topics such as trainings in economic and safe driving.

The presented work was developed in cooperation with a car manufacturer. A concrete vehicle implementation of a similar ACC-based system has recently been presented within the German research project INVENT (German Federal Ministry of Education and Research (BMBF), 2005). Note that, for a concrete implementation of the proposed traffic assistance system, one has to take into account present imperfections of ACC systems as well such as response time delays (Kranke et al., 2006). Our current work focusses on the implementation of different driving strategies and smooth transitions between them in real test vehicles. The experiences from the empirical test track data will be used to further improve the model components.

Acknowledgments:

The authors would like to thank Dr. H.-J. Stauss for the excellent collaboration and the Volkswagen AG for partial financial support within the BMBF project INVENT.

References

Bertini, R. L., Lindgren, R., Helbing, D., Schönhof, M., 2004. Empirical analysis of flow features on a German autobahn. Transportation Research Board

- Annual Meeting, Washington, D.C.
- Brockfeld, E., Kühne, R. D., Skabardonis, A., Wagner, P., 2003. Toward benchmarking of microscopic traffic flow models. *Transportation Research Record: Journal of the Transportation Research Board* 1852, 124–129.
- Cassidy, M. J., Bertini, R. L., 1999. Some traffic features at freeway bottlenecks. *Transportation Research Part B: Methodological* 33, 25–42.
- Daganzo, C., Cassidy, M., Bertini, R., 1999a. Possible explanations of phase transitions in highway traffic. *Transportation Research Part B: Methodological* 33, 365–379.
- Daganzo, C., Cassidy, M., Bertini, R., 1999b. Some traffic features at freeway bottlenecks. *Transportation Research Part B: Methodological* 33, 25–42.
- Davis, L., 2004. Effect of adaptive cruise control systems on traffic flow. *Physical Review E* 69, 066110.
- Drane, C., Rizos, C., 1998. *Positioning Systems in Intelligent Transportation Systems*. Artech House, Norwood, USA.
- German Federal Ministry of Education and Research (BMBF), 2005. Research project INVENT (Intelligent Traffic and User-Friendly Technology). <http://www.invent-online.de> – Access date: May 5, 2007.
- Green, M., 2000. "How long does it take to stop?" Methodological analysis of driver perception-brake times. *Transportation Human Factors* 2, 195–216.
- Hall, F., Wakefield, S., Al-Kaisy, A., 2000. Freeway Quality of Service: What really matters to drivers. *Transportation Research Record: Journal of the Transportation Research Board* 1776, 17–23.
- Kerner, B., Rehborn, H., 1996. Experimental features and characteristics of traffic jams. *Physical Review E* 53, R1297–R1300.
- Kerner, B. S., 2004. *The Physics of Traffic*. Springer, Heidelberg.
- Kesting, A., Treiber, M., Helbing, D., 2007a. MOBIL – A general lane-changing model for car-following models. *Transportation Research Record: Journal of the Transportation Research Board*, in print.
- Kesting, A., Treiber, M., Lämmer, S., Schönhof, M., Helbing, D., 2006. Decentralized approaches to adaptive traffic control and an extended level of service concept. In: Gürlebeck, K., Könke, C. (Eds.), *Proceedings of the 17th International Conference on the Applications of Computer Science and Mathematics in Architecture and Civil Engineering*. Bauhaus University Weimar.
- Kesting, A., Treiber, M., Schönhof, M., Kranke, F., Helbing, D., 2007b. Jam-avoiding adaptive cruise control (ACC) and its impact on traffic dynamics. In: Schadschneider, A., Pöschel, T., Kühne, R., Schreckenberg, M., Wolf, D. E. (Eds.), *Traffic and Granular Flow '05*. Springer, Berlin, pp. 633–643.
- Kranke, F., Poppe, H., Treiber, M., Kesting, A., 2006. Driver assistance systems for active congestion avoidance in road traffic (in German). In: Lienkamp, M. (Ed.), *VDI-Berichte zur 22. VDI/VW Gemeinschaftstagung: Integrierte Sicherheit und Fahrerassistenzsysteme*. Vol. 1960. Association of German Engineers (VDI), Wolfsburg, p. 375.
- Marsden, G., McDonald, M., Brackstone, M., 2001. Towards an understand-

- ing of adaptive cruise control. *Transportation Research Part C: Emerging Technologies* 9, 33–51.
- Minderhoud, M. M., 1999. *Supported Driving: Impacts on Motorway Traffic Flow*. Delft University Press, Delft.
- Rao, B., Varaiya, P., 1993. Flow benefits of autonomous intelligent cruise control in mixed manual and automated traffic. *Transportation Research Record: Journal of the Transportation Research Board* 1408, 35–43.
- Schönhof, M., Helbing, D., 2007. Empirical features of congested traffic states and their implications for traffic modeling. *Transportation Science* 41, 1–32.
- Schönhof, M., Kesting, A., Treiber, M., Helbing, D., 2006. Coupled vehicle and information flows: Message transport on a dynamic vehicle network. *Physica A* 363, 73–81.
- Schönhof, M., Treiber, M., Kesting, A., Helbing, D., 2007. Autonomous detection of jam-fronts and their anticipation from messages propagated by inter-vehicle communication. *Transportation Research Record: Journal of the Transportation Research Board*, in print.
- Treiber, M., Helbing, D., 2001. Microsimulations of freeway traffic including control measures. *Automatisierungstechnik* 49, 478–484.
- Treiber, M., Helbing, D., 2003. Memory effects in microscopic traffic models and wide scattering in flow-density data. *Physical Review E* 68, 046119.
- Treiber, M., Hennecke, A., Helbing, D., 2000. Congested traffic states in empirical observations and microscopic simulations. *Physical Review E* 62, 1805–1824.
- Treiber, M., Kesting, A., Helbing, D., 2006a. Delays, inaccuracies and anticipation in microscopic traffic models. *Physica A* 360, 71–88.
- Treiber, M., Kesting, A., Helbing, D., 2006b. Understanding widely scattered traffic flows, the capacity drop, and platoons as effects of variance-driven time gaps. *Physical Review E* 74, 016123.
- VanderWerf, J., Shladover, S., Kourjanskaia, N., Miller, M., Krishnan, H., 2001. Modeling effects of driver control assistance systems on traffic. *Transportation Research Record: Journal of the Transportation Research Board* 1748, 167–174.
- VanderWerf, J., Shladover, S., Miller, M., Kourjanskaia, N., 2002. Effects of adaptive cruise control systems on highway traffic flow capacity. *Transportation Research Record: Journal of the Transportation Research Board* 1800, 78–84.
- Varaiya, P., 1993. Smart cars on smart roads: Problems of control. *IEEE Transactions on Automatic Control* 38 (2), 195.
- Yang, X., Recker, W., 2005. Simulation studies of information propagation in a self-organized distributed traffic information system. *Transportation Research Part C: Emerging Technologies* 13 (5-6), 370–390.