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Review article

Motorway traffic flow modelling, estimation and control with vehicle automation and communication systems

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ABSTRACT

Traffic congestion on motorways is a serious threat for the economic and social life of modern society as well as for the environment, which calls for drastic and radical solutions. Conventional traffic management measures, currently applied, are valuable, but face limitations. During the last decades, a variety of vehicle automation and communication systems (VACS) have been developed and deployed, and many more are expected to appear in the near future. These systems provide a novel basis for a new generation of traffic management, which exploits emerging vehicle automation functions and connectivity channels to enable sensible traffic flow improvements in terms of efficiency and safety. A number of innovative concepts, tools and results that open up new horizons for traffic management research and practice in presence of VACS have been produced recently in the frame of TRAMAN21, an ERC Advanced Grant. This paper presents a collection of novel problems as well as of related traffic flow modelling, estimation and control developments for motorway traffic that can be used in the evolving traffic environment with VACS.

Contents

Abbreviations: ACC, Adaptive cruise control; CACC, Cooperative adaptive cruise control; CTM, Cell-transmission model; CV, Coefficient of variation; DE, Differential evolution; DP, Dynamic programming; ERC, European Research Council; FD, Fundamental diagram; FDA, Feasible direction algorithm; FIFO, First-in-first-out; GKT, Gas-kinetic traffic flow; IDM, Intelligent driver model; LCC, Lane changing control; LPV, Linear parameter varying; LQR, Linear quadratic regulator; MS, Merging sequence; MPC, Model predictive control; MTFC, Mainstream traffic flow control; NGSIM, Next Generation SIMulation; NLP, Nonlinear programming; PDE, Partial differential equation; PR, Penetration rate; QP, Quadratic programming; RM, Ramp-metering; TRAMAN21, TRAffic MANagement for the 21st century; TTT, Total travel time; TTS, Total time spent; UCO, Uniform complete observability; VACS, Vehicle automation and communication systems; V2I, Vehicle-to-infrastructure; V2V, Vehicle-to-vehicle; VMS, Variable message signs; VSL, Variable speed limit.

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1. Introduction

Traffic congestion on motorways is a serious threat for the economic and social life of modern society as well as for the environment, which calls for drastic and radical solutions. Some conventional traffic management measures currently applied may mitigate traffic congestion, but may also face various kinds of limitations. During the last decade, there has been a considerable effort to develop a variety of VACS that are expected to revolutionize the features and capabilities of individual vehicles within the next decades. Vehicles are goods manufactured and offered in a market, wherein they compete for the preference of the customers; therefore, most VACS are typically developed to benefit the individual vehicle and driver, often without a clear view or understanding for the implications, potential advantages and disadvantages they may have for the induced, accordingly modified traffic flow characteristics. From the community point of view, the gradual introduction of VACS brings along the necessity and continuously growing opportunities for accordingly adapted or utterly new traffic management actions and strategies aiming at a sensible decrease of traffic congestion and its detrimental implications for travel delays, traffic safety and the environment. It was the main objective of TRAMAN21 (www.traman21.tuc.gr), an ERC Advanced Grant, to develop foundations and first steps that pave the way towards a new era of future motorway traffic management research and practice, which is indispensable in order to accompany, complement and exploit the evolving VACS deployment.

VACS comprise on-board systems that undertake several vehicle functions at various levels of automation. Such systems, enhanced via novel communication features, aim at assisting or take on the driving task; but may also be exploited for improved traffic flow efficiency, see, Diakaki et al. (2014) and Diakaki, Papageorgiou, Papamichail and Nikolos (2015) for an overview. To this end, specific developments and options are required, particularly for network weak points, such as bottlenecks. In more detail, required contributions include the development of:

- microscopic and macroscopic traffic flow models and related simulation tools in presence of VACS;
- traffic state estimation algorithms and tools for the cross-lane case and for the per-lane case;
- traffic control algorithms and tools at various levels.

The main aim of this paper is to raise awareness and interest in novel problems and related approaches that emerge in various aspects of motorway traffic management due to the gradual introduction of VACS at increasing levels of sophistication and penetration. For each addressed area, the presentation outlines the respective motivation, essential issues and main pursued approaches in the technical literature (if any), before concentrating on the concise description of respective methods and results produced within the TRAMAN21 project. In this context, the three following sections address problems of traffic flow modelling, estimation and control, respectively.

Under the influence of vehicle automation (at different levels), the car-following and lane-changing vehicle behaviour is changing compared to manual driving. Such changes reflect also on the macroscopic characteristics of the emerging traffic flow. Section 2 discusses a microscopic simulation framework for ACC-equipped vehicles and the calibration of a microscopic traffic simulator in presence of VACS for a real large-scale motorway network. Subsequently, a macroscopic multi-lane model with ACC and CACC vehicles at various penetration rates is presented, along with a novel numerical integration approach. Finally, a discrete (in space and time) first-order macroscopic traffic flow model, to be used in model-based optimization approaches, is also outlined.

In conventional traffic, real-time measurements are provided by spot sensors (based on different technologies), which are placed at specific motorway locations and monitor traffic variables at the respective specific locations. With the introduction of connected vehicles, which may transmit information to a traffic control centre, thus acting as mobile sensors, a new era of traffic monitoring and estimation has started. In this new context, Section 3 presents a novel real-time estimation scheme, for both cross-lane and lane-based traffic variable estimation, exploiting information from connected vehicles under virtually all penetration rates.

In the VACS era, a number of further significant changes emerge, which open up new prospects for traffic management and control:

- Connected vehicles may receive advice or commands from the traffic control centre, something that reduces, and potentially eliminates, the need for road-side actuators, such as traffic signals, VMS, VSL gantries etc.
- Vehicles may receive *individual* advice or commands, something that increases control granularity, compared to road-side actuators that convey the same message to all vehicles; this also enables new control actions, such as lane assignment and lane-change control, which are not feasible with conventional means.
- Vehicles may (be asked to) behave in a way that is beneficial for the whole traffic flow, i.e., they may become part of the traffic control logic; we call this possibility *vehicle-based traffic flow control*.

Section 4 presents a selection of new opportunities for more efficient traffic control enabled by VACS. First, some developments belonging to the exciting area of vehicle-based traffic flow control are presented, including: cooperative merging at motorway on-ramps; automated vehicle trajectory optimization; ACC-vehicle control for improved traffic flow; and feedback-based lane assignment. Subsequently, an integrated network-wide control approach is outlined, exploiting novel opportunities offered by VACS. Specifically, an optimization-based traffic control approach was developed, wherein the presence and use of VACS permits the implementation of an increased range of control actions in an integrated synergistic way. The obtained test results show significant improvements enabled by the combined use of VACS. Finally, a number of other applications are briefly touched upon. Section 5 concludes the overview of developed methods.

2. Traffic flow modelling

Since the penetration rate and sophistication level of VACS are still low, real data are sparse, and the main way to investigate their future impact on the traffic flow or to design, test and demonstrate novel traffic control approaches for various scenarios of VACS types, presence and use is modelling and simulation. This marks the very basic need of developing new or expanding existing traffic flow modelling and simulation methods and tools that account for the VACS presence. It must be emphasized that models are tools, which provide a necessary basis for a variety of different tasks, each requiring a different level of model granularity, accuracy or computational effort. Thus, in the following subsections, different traffic flow models (in presence of VACS) are presented, which serve as valuable tools for different purposes of motorway traffic management.

2.1. Microscopic modelling

Microscopic simulators are very useful and widely adopted tools for the analysis and management of transportation systems. However, when vehicles equipped with various kinds of VACS at various penetration levels are present in the traffic flow, there are no ready available simulation tools for immediate use. Different open-source (e.g., SUMO, see, Lopez et al., 2018) or commercial microscopic traffic simulators provide to the user the possibility to introduce self-developed car-following and lane-changing models, which reflect the modified behaviour of equipped vehicles. In the works reviewed in this paper, most reported microscopic simulation investigations are based on Aimsun (TSS-Transport Simulation Systems, 2014), which provides the necessary tools for introducing the VACS presence by coding self-developed vehicle models. Similar possibilities are also available with other commercial simulators, such as VISSIM, see Aria, Olstam and Schwietering (2016).

2.1.1. Adaptive cruise control impact

The control objectives of an ACC system are (Shladover, Su & Lu, 2012):

- *Speed control mode:* to travel close to the pre-set (by the driver) desired speed, in cases where no leading vehicle is detected by the vehicle's sensors; or a leading vehicle is detected but its speed is higher than the driver-defined desired speed.
- *Gap control mode:* to adjust the speed of the equipped vehicle to the speed of the leading vehicle and maintain the user-defined desired time-gap to the leading vehicle, in cases that a leading vehicle is identified by the sensors, and its speed is lower than the pre-set by the user desired speed.

Several works investigated the influence of ACC systems on traffic flow, attempting to capture the impact of different settings (mainly different time-gaps) and penetration rates, by use of microscopic simulation, see e.g., Arnaout and Bowling (2011), Bayar, Sajadi-Alamdari, Viti and Voos (2016), Schakel, Van Arem and Netten (2010) and Shladover et al. (2012). General conclusions that may be drawn from those studies are that: (i) ACC systems have the potential to improve or deteriorate, depending on their settings, the traffic conditions compared to the case of conventional manually driven vehicle traffic; and (ii) the level of the influence is closely related to the ACC penetration rate. In particular, Ntousakis, Nikolos and Papageorgiou (2015) reviewed previous modelling efforts reported in the literature, concerning ACC-equipped vehicles, and discussed some critical aspects to be considered when designing or simulating such systems. Moreover, a microscopic simulation framework for ACC-equipped vehicles was developed within the Aimsun microscopic traffic flow simulator, utilizing its so-called API and MicroSDK tools. Simulation experiments have been performed to examine:

(a) the impact of ACC on traffic flow capacity for different penetration rates and different ACC time-gap settings for a single-lane open-stretch road; and
(b) the effect of ACC on preventing the formation of stop-and-go waves in a ring-road.

For simulating manually driven vehicles, two different car-following models were employed, the one by Gipps (1981) and IDM (Treiber, Hennecke & Helbing, 2000). The simulation results for case (a) showed that the ACC time-gap has a direct impact on the capacity: the smaller the time-gap, the higher the capacity, and vice-versa. Thus, the traffic flow capacity can be increased if the ACC time-gap is smaller than that of manual vehicles; else deterioration of capacity may occur. Fig. 1 illustrates that, when ACC and manual vehicles have a similar time-gap (here around 1.1 s), then the ACC vehicles have no influence on capacity for any penetration rate. However, if the ACC time-gap is higher (lower) than that employed by manual vehicles, then any increase of the ACC penetration leads to a decrease (increase) of capacity; and the potential changes at both ends of the spectrum are indeed substantial. These results highlight the need and potential for appropriate use of ACC systems with regard to traffic management, as discussed in Section 4.3.

For the case (b), it was observed that ACC vehicles may improve the stability of traffic flow, since they mitigate string-instability

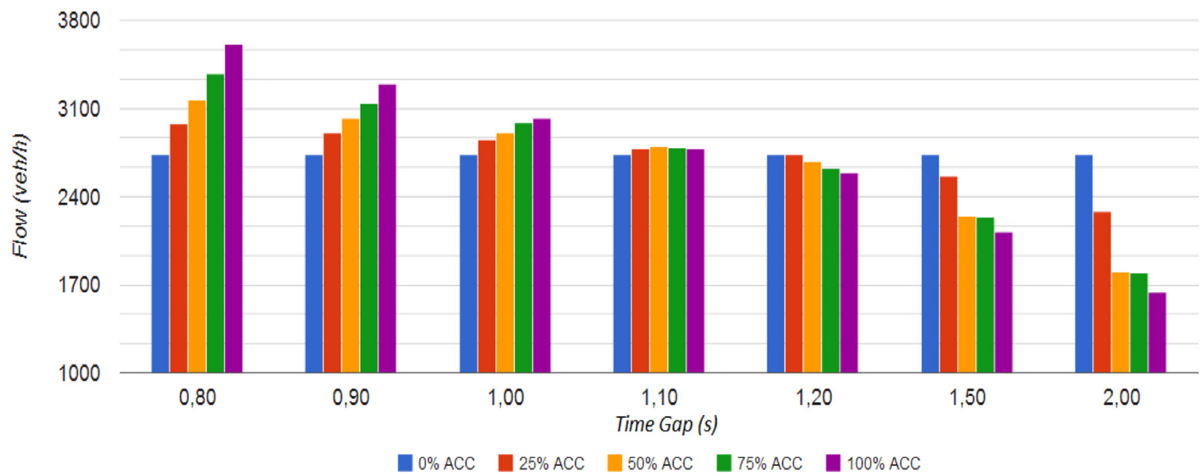

Fig. 1. Traffic flow capacity (veh/h/lane) for different ACC time-gaps and different ACC penetration rates.

and hence the amount and intensity of stop-and-go waves. Such observations were indeed made also in other similar works, indicating that ACC systems have the potential to smooth traffic flow, decrease fuel consumption, and improve traffic flow efficiency (Ioannou & Stefanovic, 2005; Ngoduy, 2012). However, it should be stressed that the real dynamic behaviour of real ACC vehicles is not well-known and hence not necessarily well-captured in microscopic simulation studies that are based on idealized ACC time-gap regulators. In fact, some more recent studies (Gunter et al., 2019; Gunter, Janssen, Barbour, Stern & Work, 2019; Milanés & Shladover, 2014), employing data from real ACC vehicles, indicate that real ACC vehicles may behave (like manually-driven vehicles) in a string-unstable way. Corresponding model identification exercises for ACC vehicles using real data may enable more realistic assessment of the impact of ACC systems on the traffic flow.

2.1.2. Microscopic model calibration

Microscopic simulation is a valuable tool for assessment of novel control strategies that exploit VACS of various kinds. Although there is some uncertainty regarding the exact dynamic behaviour of equipped vehicles, a microscopic simulator should provably reflect with sufficient accuracy the traffic flow resulting when only manually driven vehicles are considered. Calibration and validation of microscopic models by use of real data for conventional traffic has been the subject of many recent studies, see e.g., Toledo, Ben-Akiva, Darda, Jha and Koutsopoulos (2007) and Treiber and Kesting (2012). In order to produce a simulation-based testbed for a variety of traffic control investigations, a thorough calibration of a microscopic multi-lane traffic flow model for a real sizable motorway was carried out by Perraki, Roncoli, Papamichail and Papageorgiou (2018). The modelled network is a 12 km-long stretch of the motorway A20, from Rotterdam to Gouda, The Netherlands (Fig. 2(a)). Its topological and traffic characteristics (it includes a lane-drop, strong merging flow from on-ramps and partly saturated off-ramps) make it a very interesting testbed for investigating various different scenarios with and without the presence of VACS. The microscopic simulator Aimsun was used, with critical additions and adaptations made in order to improve the realism of the simulation and enable it to reproduce complex traffic phenomena (e.g., the capacity drop at the head of congestion). More specifically, different new features were introduced, including the IDM car-following model (Treiber et al., 2000) as well as improved heuristic rules to capture more accurately the lane-changing behaviour in the proximity of on-ramps and lane-drops (vehicle merging). Fig. 2(b) illustrates the similarity of the real data and model outcome, respectively, in terms of mean speed. Note that the shock wave entering the stretch from the downstream boundary in Fig. 2(b-upper) is not reproduced by the model, which was intentionally not fed with the corresponding boundary conditions to avoid interference with congestion triggers that are not included in the considered stretch.

This model was eventually enriched with features related to VACS (e.g., connected vehicles, partially and fully automated cars) and was used for testing the accuracy of proposed macroscopic models (see Section 2.2), estimation tools (see Section 3), as well as various proposed control strategies (see Section 4).

2.2. Macroscopic modelling

Macroscopic models characterize traffic in terms of aggregate density, space-mean speed, and flow, as opposed to microscopic ones that describe interactions between individual vehicles Macroscopic traffic flow modelling has a long history, see (Hoogendoorn & Bovy, 2001) for a review. Macroscopic models are valuable for traffic management purposes, because, except for their use as efficient simulators (see e.g., Papageorgiou, Papamichail, Messmer & Wang, 2010), they are analytic in nature and may therefore provide a solid basis for the application of modern estimation and control tools, see, Kotsialos and Papageorgiou (2001). In the context of VACS, conventional macroscopic models need to be appropriately modified and extended. To start with, the modified microscopic behaviour of equipped vehicles, appearing in different penetrations, reflects into accordingly modified macroscopic traffic behaviour, which needs to be captured not merely via modified model parameters, but also via structural changes in the model equations. In addition, VACS enable utterly new control measures, such as lane-change commands to individual vehicles, which are not possible in conventional traffic. To support the design and testing of such lane-change control strategies, macroscopic models need to be lane-based, i.e., able to describe not only longitudinal flow, but also lateral (lane-changing) flow, something very rare in conventional traffic flow modelling.

Available conventional macroscopic models feature significant differences in complexity and potential accuracy. Macroscopic models may be first-order (comprising one PDE) or second-order (two PDEs) or higher-order. For the convenience and computational efficiency of their application, macroscopic models may be discrete in space and time, i.e., comprise a number of difference state equations instead of PDEs. Clearly, like in other domains, there is no best model form for any use; rather the most appropriate macroscopic model form depends on its intended use.

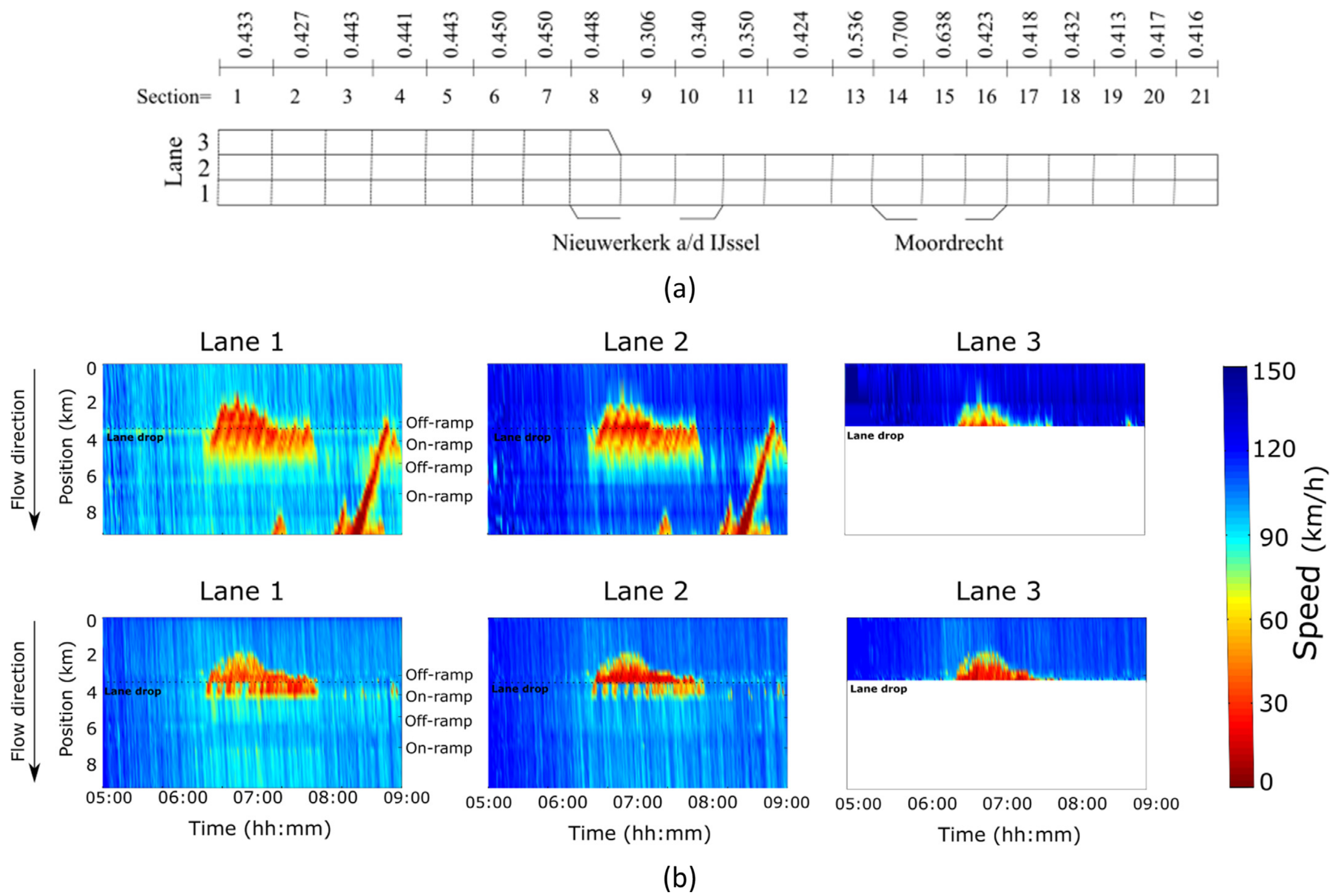

Fig. 2. (a) A real motorway testbed; (b) Space-time plot of mean speed (real data – upper row – and microscopic model – lower row).

The outlined variety of different conventional macroscopic models reflects also in their extension for the case of VACS presence and is probably a reason why macroscopic model developments including VACS are still scarce. In the following, a PDE-based second-order macroscopic multi-lane traffic flow model with ACC and CACC vehicles at various penetration rates is presented first. Then, a simpler discrete first-order multi-lane macroscopic traffic flow model, to be used in model-based optimization approaches is outlined.

2.2.1. Second-order modelling in presence of VACS

Essentially, macroscopic models are governed by the continuity equation, which is derived from vehicle conservation and describes the evolution of density based on flow gradients. In addition, second-order models include a second PDE to describe how speed changes dynamically. Some parameters from this second equation can be used to differentiate the characteristics between manual vehicles and those equipped with ACC or CACC systems. Although the literature following this modelling approach is rather limited, the approach has been used to model ACC (Wang & Rajamani, 2004; Yi & Horowitz, 2006), V2V communication (Ngoduy & Jia, 2017; Zheng, Jin & Huang, 2015) and CACC (Ngoduy, 2013, 2009). Although most of literature following this approach focuses on homogeneous traffic, i.e., assuming 100% penetration rate, there exist some very recent attempts that consider varying penetration rates of ACC or CACC systems (Ngoduy, 2012).

In this section, we present a PDE-based multi-lane GKT traffic flow model (Delis, Nikolos & Papageorgiou, 2014; Shvetsov & Helbing, 1999; Treiber & Kesting, 2013) extended with ACC or CACC modelling terms to account for the effect on traffic dynamics of variable penetration rates of ACC or CACC vehicles, as well as of different classes of drivers using different time-gaps. In a highway with N lanes, numbered by $l = 1, 2, ..., N$, with $l = 1$ being the slowest lane, we aim to model the evolution, in space x and time t, of traffic density (number of vehicles per unit length) $\rho_l(x, t)$ and traffic flow rate (number of vehicles per unit of time) $q_l(x, t) = \rho_l u_l$, with $u_l(x, t)$ being the mean speed of vehicles in the lth lane. To this end, the extended ACC/CACC multi-lane GKT model may be written for each lane l as

$$\partial_t \rho_l + \partial_x q_l = \sum_{k=1}^{m} \rho_{rmp,k} \delta_{j,1} + w_l^{(1)} \tag{1}$$

$$\partial_t q_l + \partial_x \left(q_l^2/\rho_l + \theta_l \rho_l \right) = \sum_{k=1}^{m} h_{rmp,k} \delta_{l,1} + w_l^{(2)} + \left(\frac{\rho_l V_{e,l}^* - q_l}{\tau_l} \right) [1 - PF_l(\rho_l)] + P\mathcal{V}_{(c)acc,l} \tag{2}$$

$$\rho_l(x, 0) = \rho_{l,\ 0}(x);\ q_l(x, 0) = q_{l,\ 0}(x), \quad l = 1,\ 2, \ldots, N. \tag{3}$$

System (1)–(3) constitutes a weakly coupled system of conservation laws, with a total of $2N$ equations, for traffic density and flow for each lane. In what follows, definitions and explanations related to these equations are provided step-by-step:

The core multi-lane model: In the momentum (flow) Eq. (2), we introduce the modelling terms that account for the ACC or CACC vehicles in the flow, namely the terms $[1 - PF_l(\rho_l)]$ and $PV_{(c)acc,\ l}$. The parameter P in these terms accounts for the penetration rate of ACC or CACC vehicles. For $P = 0$, the original multi-lane GKT model for manually driven vehicles is recovered. In the flux term of Eq. (2), $\theta_l\rho_l$ represents a pressure-like term, where $\theta_l = A_l(\rho_l)u_l^2$ with $A_l(\rho_l)$ being a density-dependent variance factor given by the Fermi function as $A_l(\rho_l) = A_{0,l} + \delta A_l[1 + \tanh((\rho_l - \rho_{cr,l})/\delta\rho_l)]$, where $\rho_{cr,\,l}$ is the critical density for the lth lane, with $A_{0,\,l}$ and $A_{0,l} + 2\delta A_l$ the variance pre-factors between the two states; while $\delta\rho_l$ denotes a transition density width. Typical range of values for the constants $A_{0,\,l}$, δA_l and $\delta\rho_l$ along with the typical range of the other parameters for this model can be found in Delis et al. (2014), Delis, Anargiros, Nikolos and Papageorgiou (2018), 2015a and Ngoduy (2013). Term $\rho_{rmp,\,k}$ ($h_{rmp,\,k}$) models the incoming (outgoing) traffic flow from the $k$thon-ramp (or to the $k$thoff-ramp) on the first lane.

The model also includes a (non-local) relaxation term in the flow Eq. (2) aiming to keep flow in equilibrium at each lane. We denote with $V_{e,l}^* \equiv V_e^*(\rho_l, u_l, \rho_{\alpha,l}, u_{\alpha,l})$ the non-local and dynamic equilibrium speed, with τ_l being a relaxation time. $V_{e,l}^*$ depends not only on the local lane density ρ_l and mean speed u_l, but also on a non-local density $\rho_{a,\,l}$ and mean speed $u_{a,\,l}$, and is defined as

$$V_{e,l}^* = u_{\max,l}\left[1 - \frac{\theta_l + \theta_{\alpha,l}}{2A_l\left(\rho_{\max,l}\right)}\left(\frac{\rho_{\alpha,l}T_l}{1 - \rho_{\alpha,l}/\rho_{\max,l}}\right)^2 B(\delta u_l)\right]. \tag{4}$$

$V_{e,l}^*$ is given by the maximum lane velocity $u_{\max,\,l}$, reduced by a term that reflects necessary deceleration maneuvers. Both $\rho_{\alpha,\,l}$ and $u_{\alpha,\,l}$ are computed at an anticipated location $x_{\alpha,l} = x_l + \gamma_l(1/\rho_{\max,l} + T_l u_l)$ with T_l being the desired time-gap for manual driving, $\rho_{max,\,l}$ the maximum lane density and γ_l a scale factor. Finally, B is a so-called Boltzmann (interaction) factor, which, with $\delta u_l = (u_l - u_{a,l})/(\sqrt{\theta_l - \theta_{\alpha,l}})$, is determined as

$$B(z) = 2\left[z\frac{e^{-z^2/2}}{\sqrt{2\pi}} + \left(1 + z^2\right)\int_{-\infty}^{z}\frac{e^{-y^2/2}}{\sqrt{2\pi}}dy\right]. \tag{5}$$

Multi-lane terms: The basic assumptions that the multi-lane model aims to satisfy, in terms of vehicles' interactions are: (a) changing to the left; (b) changing to the right; (c) breaking; (d) acceleration-following; (e) acceleration-free flow (Delis et al., 2018; Delis, Nikolos & Papageorgiou, 2015b). To this end, source terms $w_l^{(1),(2)}$ in the model equations account for the sources and sinks due to lane-changing for the quantities $v_l^{(1)} = \rho_l$ and $v_l^{(2)} = q_l$ that satisfy the above assumptions

$$\begin{aligned} w_l^{(1),(2)} = &\left(\frac{1}{T_{l-1}^L}v_{l-1}^{(1),(2)} - \frac{1}{T_l^R}v_l^{(1),(2)}\right)\left(1 - \delta_{l,1}\right) \\ &+ \left(\frac{1}{T_{l+1}^R}v_{l+1}^{(1),(2)} - \frac{1}{T_l^L}v_l^{(1),(2)}\right)\left(1 - \delta_{l,N}\right) \end{aligned} \tag{6}$$

where terms $1/T_l^L$ and $1/T_l^R$ are the lane changing rates from lane l to the left $l+1$ and right $l-1$ lane, respectively, and $\delta_{i,\,j}$ the Kronecker delta. These rates are given as

$$\begin{aligned} \frac{1}{T_l^L} &= P_L(\rho_{l+1})\sigma(\rho_l) + S_l^L, \\ \frac{1}{T_l^R} &= P_R(\rho_{l-1})(1 - P_L(\rho_{l+1}))\sigma(\rho_l) + S_l^R, \end{aligned} \tag{7}$$

with $P_{R,\,L}(\rho)$ being the lane-changing probabilities due to vehicle interactions and $\sigma(\rho) = \sigma_f(1 - \rho_l)\rho_l^2$ denote the interaction frequencies regarding decelerations and accelerations.

Furthermore in (7) we take into account spontaneous lane changes, which are not caused by interactions with other vehicles, through the terms $S_l^{L,R}$. We assume that these terms depend on the density, ρ_l, and are given as

$$S_l^{L,R} = k_l^{L,R}\left(1 - \frac{\rho_{l\pm1}}{\rho_{\max,l\pm1}}\right)^\beta \tag{8}$$

where $k_l^{L,R}$ and β are spontaneous lane-changing parameters.

The ACC/CACC terms: Terms $[1 - PF_l(\rho_l)]$ and $PV_{(c)acc,\,l}$in the flow Eq. (2) are related to the extension of the multi-lane model, so as to incorporate the effects of ACC/CACC in traffic dynamics. The control objectives of an ACC/CACC system, mentioned earlier, should be satisfied here (Delis, Nikolos & Papageorgiou, 2016; Nikolos, Delis & Papageorgiou, 2015).

At densities below a threshold $\rho_{acc,\,l}$ (being lower than or equal to the critical lane density $\rho_{cr,\,l}$), the additional term to the multi-lane GKT model has no influence, since it is assumed that the vehicles apply the desired speeds as in manual driving. At densities around $\rho_{acc,\,l}$, a smooth but fast transition between the previous manual case and the ACC or CACC model is established, using the Fermi-like function $F_l(\rho_l) = 0.5[1 + \tanh((\rho_l - \rho_{acc,l})/\Delta\rho_l)]$ with $\Delta\rho_l \approx 0.025\rho_{\max,\,l}$. As a result, the corresponding source for ACC vehicles in each lane reads

$$V_{acc,l}\left(\rho_l, u_l, \rho_l^*, u_l^*\right) = F_l(\rho_l)\left(\frac{\rho_l^* u_l^* - \rho_l u_l}{\tau_l^*}\right) \tag{9}$$

which forces the speed to relax to the speed of the preceding vehicle u_l^* after a relaxation time τ_l^*. Assuming that different classes of drivers choose different desired time-gaps, we denote ω_j, $j = 1, \ldots, Nclass$, the percentage of drivers with different time-gaps T_j^*. These gaps can be imposed through their corresponding influence on a desired lane density ρ_l^* in (9), that is given as:

$$\rho_l^* = \frac{1}{\left(1/\rho_{max,l} + \sum_{j=1}^{Nclass}\omega_j T_j^* u_{j,l}^*\right)} \tag{10}$$

where $u_{j,l}^* \equiv u(x_{j,l}^*)$ is evaluated at location $x_{j,l}^* = x_l + \gamma_l^*(1/\rho_{max,l} + T_j^* u_l)$ and the mean preceding vehicle speed in (9) $u_l^* = \sum_{j=1}^{Nclass}\omega_j u_{j,l}^*$. Indicative values used for ACC traffic are $T^* \in [0.8, 2.2]$s, following [ISO 15622, 2010] standards, and $\tau^* \approx 1$s.

To model the impact of CACC vehicles in traffic flow dynamics, a similar approach is utilized, with the only difference being that a vehicle can exchange information with M preceding vehicles, each of which has a different relaxation time. Thus, the corresponding source term of the momentum equation for lane l takes now the form

$$V_{cacc,l}\left(\rho_l, u_l, \rho_l^*, u_l^*\right) = F_l(\rho_l)\sum_{i=1}^{M}\left(\frac{\rho_l^* u_l^* - \rho_l u_l}{\tau_l^*}\right) \tag{11}$$

where now

$$\rho_l^* = \frac{1}{\left(1/\rho_{max,l} + \sum_{j=1}^{Nclass}\omega_j T_j^* u_{j,1,l}^*\right)}, \qquad u_{i,l}^* = \sum_{j=1}^{Nclass}\omega_j u_{j,i,l}^* \tag{12}$$

with $u_{j,i,l}^* \equiv u_l(x_{j,i,l}^*)$ at location $x_{j,i,l}^* = x_l + i\gamma_l^*(1/\rho_{\max,l} + T_j^* u_l)$. For example, for CACC systems, one can assume that $M = 3$, while $[\tau_{1,l}^*, \tau_{2,l}^*, \tau_{3,l}^*] = [2, 3, 6]$ as in (Delis et al., 2015b, 2016; Delis et al., 2018).

The numerical integration of the PDE model equations is based on an accurate and robust higher-order finite-volume relaxation scheme. A fifth-order weighted essential non-oscillatory-type interpolant approach is used for the spatial discretization, while time integration is based on a third-order implicit-explicit Runge–Kutta method (Delis et al., 2014, 2015b).

The developed macroscopic model has been used to simulate traffic flow for either manual or ACC/CACC or mixed vehicle traffic, in single-lane or multi-lane highways (Delis et al., 2016, 2018; Nikolos et al., 2015; Porfyri, Delis, Nikolos & Papageorgiou, 2017, 2016; Strofylas, Porfyri, Nikolos, Delis & Papageorgiou, 2018). In the work by Delis et al. (2018), the multi-lane second-order GKT model, extended with the modelling of ACC/CACC vehicles was presented and evaluated. A real motorway network has been used as a test-case, where a recurrent congestion occurs, and for which real traffic measurements are available for manual traffic. The main parameters of the multi-lane GKT model for manual driving were calibrated and validated; eventually, keeping these parameters fixed, simulations were conducted for various penetration rates of ACC and CACC vehicles, assuming a constant time-gap, which was different for each case. The numerical simulations demonstrate that ACC systems with low time-gap may mitigate congestion at bottlenecks at an extent that depends on their penetration rate; and that CACC systems lead to higher efficiency at the same penetration rates. In Strofylas et al. (2018), numerical simulations have been presented using real traffic data from a freeway stretch of Attiki Odos motorway, Greece, where recurrent congestion occurs during the morning peak hours. A parallel, synchronous or asynchronous, metamodel-assisted DE algorithm was employed for the calibration of the second-order macroscopic GKT model. Two Artificial Neural Networks, a multi-layer perceptron and a radial basis function network, were used as surrogate models to decrease the computation time of the evaluation phase of the DE optimizer. The obtained results demonstrate that the proposed model is reasonably accurate in reproducing traffic dynamics, while the parallel DE algorithm can be effectively used for its calibration.

2.2.2. Control-oriented motorway traffic modelling

As mentioned earlier, macroscopic models may serve different purposes, some of which require availability of simpler than PDE-based models to enable higher computational efficiency and methodological simplicity. Network-wide integrated traffic control strategies employing, beyond conventional ramp metering, appropriate VACS-based actuators, such as vehicle speed control and lane-assignment or lane-changing recommendations in the aim of mitigating motorway traffic congestion are presented in Section 4. To enable some of these approaches by use of optimal control methods, an appropriate low-complexity traffic flow model is needed, both for control strategy design and as a no-control base case for comparative evaluation studies.

Such a multi-lane first-order space-time discrete model was built starting from the well-known CTM (Daganzo, 1994), which was modified and extended to consider additional important aspects of the traffic dynamics, such as lane changing and the capacity drop. The model was derived with a view to combine realistic traffic flow description with a simple discrete piecewise-linear mathematical structure, which can be exploited for efficient optimal control problem formulations, as well as for the development of advanced model-based nonlinear feedback control concepts, as will be reported in Section 4. Although the model was primarily designed for use in future traffic conditions including VACS, it may also be employed, with appropriate parameter values, for conventional traffic flow representation. The accuracy of the simple model was demonstrated through calibration and validation procedures using conventional real data from an urban motorway located in Melbourne, Australia, see, Roncoli, Papageorgiou and Papamichail (2015b and Section 4.5 for more details.

Regarding, in particular, the crucial phenomenon of capacity drop, it is well-known that classic first-order traffic flow models are not able to reproduce it. Therefore, various research groups investigated different possibilities of including capacity drop in a first-order traffic flow model (Ferrara, Sacone & Siri, 2015; Li, Liu, Xu & Wang, 2016; Manolis, Papamichail, Kosmatopoulos & Papageorgiou, 2016; Muralidharan & Horowitz, 2015; Ngoduy, 2012; Torné, Soriguera & Geroliminis, 2014). To comprehensively address this fundamental issue, some modelling approaches presented in the literature, together with some novel approaches, were analysed, with particular emphasis on the practical applicability of such models for traffic management and control. A subset of the most promising modelling approaches was thoroughly tested, calibrated and compared using real data from a motorway network in U.K., and the obtained results, reported in (Kontorinaki, Spiliopoulou, Roncoli & Papageorgiou, 2017), may guide the proper choice of a simple traffic flow model for use in various traffic control endeavours.

3. Traffic state estimation using connected vehicle data

The availability of real-time data is a prerequisite for traffic management and control. Spot detectors are conventionally used, but they are costly to acquire, install and maintain; while the data they provide are local, rather than spatial, as required by traffic control strategies. Abundant information stemming from equipped vehicles may be used to reduce the cost and increase the accuracy of real-time information. In fact, with the introduction of VACS of various kinds, an increasing number of vehicles become “connected,” i.e., enabled to send (and receive) real-time information to a local or central monitoring and control unit. Thus, connected vehicles may communicate their position, speed and other relevant information, i.e., they can act as mobile sensors. The transforming of such information into real-time estimates for the traffic states calls for appropriate estimation schemes, and various research works attempt to exploit these data for travel time or highway state estimation; employing various kinds of traffic models and estimation schemes, see e.g., Deng, Lei & Zhou (2013), Herrera and Bayen (2010), Piccoli, Han, Friesz, Yao and Tang (2015), Seo, Kusakabe and Asakura (2015) and Yuan, Van Lint, Van Wageningen-Kessels and Hoogendoorn (2014). These estimation approaches involve some sort of empirical traffic flow modelling, typically a fundamental diagram, which calls for appropriate model calibration and validation to the specific highway traffic conditions prior to deployment. An alternative estimation approach was developed by Bekiaris-Liberis, Roncoli and Papageorgiou (2016), which employs only exact traffic flow physical laws, such as the conservation-of-vehicles equation, which eliminates the need for model calibration prior to usage. The method exploits position and speed data from connected vehicles, as well as total flow measurements obtained from a minimum number of fixed detectors using a time-variant Kalman filter. Observability of the underlying model and stability of the estimators are rigorously addressed. Cross-lane and per-lane traffic state estimation schemes are developed and validated using both real data and data generated via microscopic simulation.

3.1. Cross-lane estimation

3.1.1. Traffic density dynamics

The discrete-time dynamics of total densities ρ_i of vehicles in N highway segments are given by the conservation equation

$$\rho_i(k+1) = \rho_i(k) + \frac{T}{\Delta_i}(q_{i-1}(k) - q_i(k) + r_i(k) - s_i(k)), \tag{13}$$

where, for all traffic variables, we denote by index i their value in segment i; q_i is the total flow; T is the time step, Δ_i is the length of segment i, and $k = 0, 1, \ldots$ is the discrete time index. The variables r_i and s_i denote the unmeasured inflow and outflow of vehicles at on-ramps and off-ramps, respectively, whose dynamics may be reflected by a random walk. Thus, using the known relation

$$q_i = \rho_i v_i, \tag{14}$$

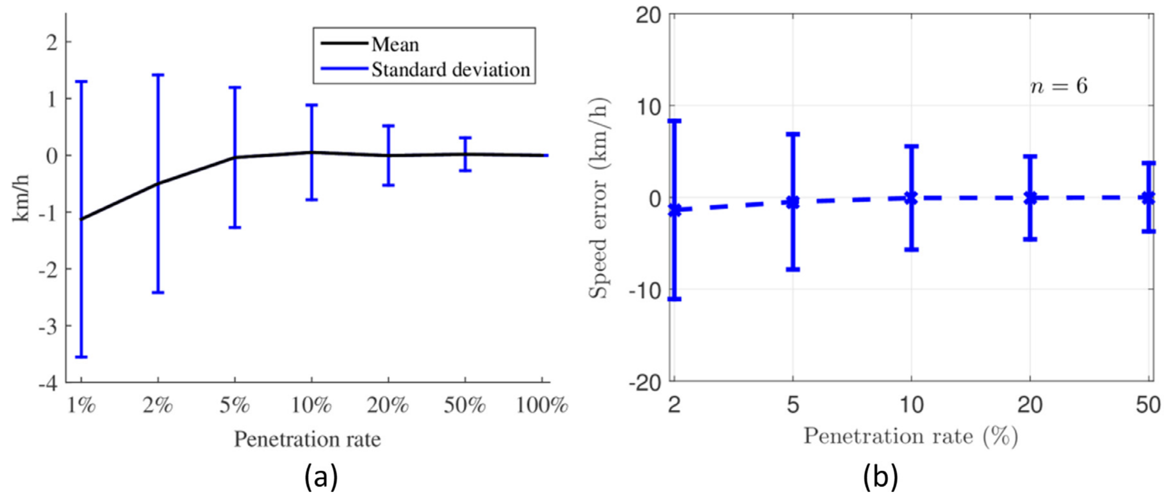

Fig. 3. Mean and standard deviation of the speed error (connected-vehicles versus all-vehicles speed) as the penetration rate of connected vehicles varies. (a) The case of NGSIM data; (b) The case of data generated in microscopic simulation.

where v_i is the mean speed in segment i, we get

$$\rho_i(k+1) = \frac{T}{\Delta_i} v_{i-1}(k)\rho_{i-1}(k) + \left(1 - \frac{T}{\Delta_i} v_i(k)\right)\rho_i(k) + \frac{T}{\Delta_i}\theta_i(k), \theta_i(k+1) = \theta_i(k), \tag{15}$$

with $\theta_i = r_i - s_i$. Assuming that the mean speed of all vehicles is not systematically different from the average speed of connected vehicles, denoted by v_i^c, and defining $x = (\rho_1, \ldots, \rho_N, \theta_1, \ldots, \theta_N)^T$, system (15) can be written in the form of a linear parameter-varying system of the form

$$x(k+1) = A(v^c(k))x(k) + Bu(k), y(k) = Cx(k), \tag{16}$$

for appropriate A, B, C where u is the measured mainstream inflow, and y consists of a minimum amount of measured flows, which are necessary to guarantee observability; all these flow measurements are obtained from fixed flow detectors.

3.1.2. Estimation scheme

For estimating vector x, we employ a Kalman filter (see e.g., Cha, Rotkowitz & Anderson, 2008) using model (16) and measurements v^c, y, u. As mentioned, a main assumption of the estimation approach is that the average of speed measurements stemming from connected vehicles reports is representative of the all-vehicles average speed. Fig. 3 validates this assumption, showing the noise statistics derived for the speed measurement error using both real data (specifically, the processed by Montanino and Punzo (2013) real microscopic traffic data collected within the NGSIM program, US DoT, 2005) as well as traffic data generated using microscopic simulations (namely, simulations in Aimsun see, Fountoulakis, Bekiaris-Liberis, Roncoli, Papamichail & Papageorgiou, 2017, for details).

3.1.3. Observability and stability

To guarantee the stability of the estimation scheme Bekiaris-Liberis et al., 2016), the most crucial element is establishing the UCO property of system ((16). Assuming that the mean speeds are nonzero for all times, it can be shown, using an algebraic or a graph-theoretic approach Bekiaris-Liberis et al., 2016; Bekiaris-Liberis, Roncoli & Papageorgiou, 2017), that ((16) is UCO when a fixed flow detector is placed, in addition to the highway mainstream exit and entry, at every segment immediately upstream a ramp whose flow is unmeasured, as illustrated in Fig. 4(a). In practice, observability is guaranteed when a fixed flow detector is placed anywhere between two consecutive unmeasured ramps (Bekiaris-Liberis et al., 2017).

3.1.4. Case studies

Real data validation using NGSIM data: We employ NGSIM traffic data (see Section 3.1.2) for a 400-m stretch of highway I-80, Emeryville, California. The stretch is divided into 8 homogeneous segments of 50 m in length, and an on-ramp is located within the fourth segment. All necessary information needed for estimation is extracted from the available vehicle trajectory data, i.e., v^c(computed as average of speeds of a subset of vehicles randomly tagged as connected), y, u. For brevity, only results for 5% penetration rate are shown in Fig. 5; see Roncoli, Bekiaris-Liberis and Papageorgiou (2016b) for details.

Microscopic simulation-based validation: For various percentages of connected vehicles, we use as evaluation metric the CV of the root mean square error between real and estimated densities. We show in Fig. 6 estimation results for a realistic scenario in a sizable network, consisting of a 10-km, three-lane highway stretch with several on/off-ramps, under various traffic conditions, utilizing the microscopic traffic simulation software Aimsun. It may be seen from Fig. 6 that the accuracy of the estimation scheme does not degrade substantially even for very low penetration rates, see, Fountoulakis et al. (2017) for details.

3.2. Per-lane estimation

Real-time traffic information per lane is crucial for the implementation of some novel, VACS-enabled traffic control measures, such as lane assignment and lane-change control. To the best of our knowledge, the estimation approach presented in this section is the only one in the technical literature to address the problem of per-lane estimation.

3.2.1. Traffic density dynamics

We provide the discrete-time dynamics of per-lane densities based on the conservation equation for each segment-lane cell (i, j) as

$$\rho_{i,j}(k+1) = \rho_{i,j}(k) + \frac{T}{\Delta_i}\big(q_{i-1,j}(k) - q_{i,j}(k) + L_{i,j-1\to j}(k) + L_{i,j+1\to j}(k) - L_{i,j\to j-1}(k) - L_{i,j\to j+1}(k) + r_{i,j}(k) - s_{i,j}(k)\big), \tag{17}$$

where $\rho_{i,j}$ is the total traffic density in cell (i, j); $q_{i,j}$ is the total longitudinal inflow entering cell $(i+1, j)$; $r_{i,j}$ and $s_{i,j}$ are the

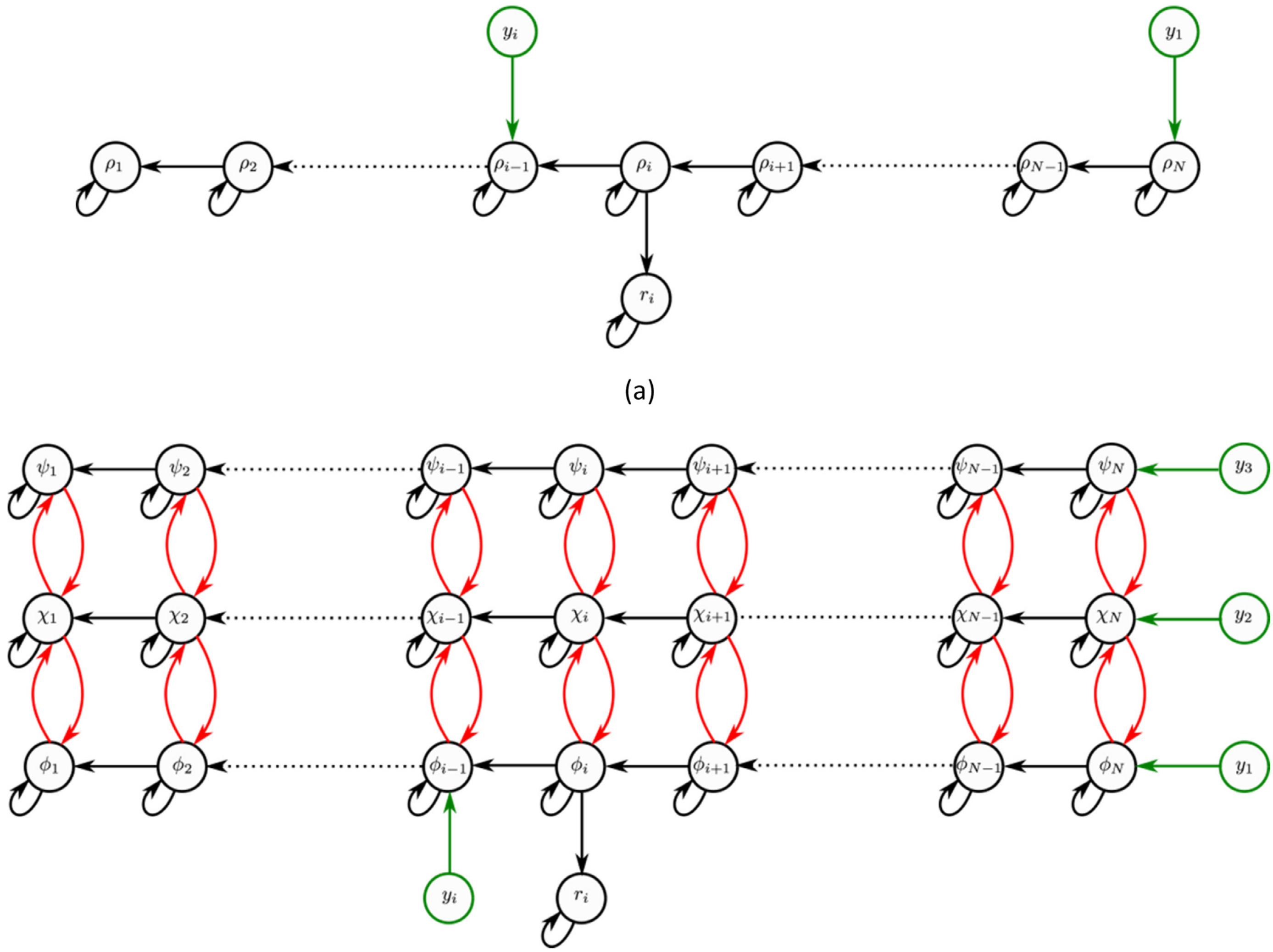

Fig. 4. (a) Graph of system (16); (b) Graph of system (20). Green vertices denote measured states and directed arcs indicate reverse traffic flow, which exist when the corresponding elements of the matrices are nonzero.

total on- and off-ramp flows entering and exiting from cell (i, j), respectively; and $L_{i,j_1\to j_2}$ is the total lateral (lane-changing) flow at segment i that enters lane j_2 from lane j_1.

We assume in our model that the following relations hold

$$q_{i,j}(k) = v_{i,j}(k)\rho_{i,j}(k) + p_{i,j-1\to j}L_{i,j-1\to j}(k) + p_{i,j+1\to j}L_{i,j+1\to j}(k) + \bar{p}_{i,j}r_{i,j}(k), \tag{18}$$

$$L_{i,j_1\to j_2}(k) = \frac{L^c_{i,j_1\to j_2}(k)}{\rho^c_{i,j_1}(k)}\rho_{i,j_1}(k) \tag{19}$$

where $p_{i,j_1\to j_2}, \bar{p}_{i,j} \in [0, 1]$ are parameters that indicate the percentages of "diagonal" lateral movements and ω^c represents the measurement involving only connected vehicles of variable ω. The first term in (18) is the same as in (14), while the rest terms are motivated by the fact that, at locations featuring strong lateral flows (e.g., at on-ramps or lane-drops), the flow is more accurately described by considering that a percentage of lateral or on-ramp flows acts as additional exiting longitudinal flow (i.e., flow may also move diagonally). Relation (19) is based on the reasonable assumption that the average behaviour of the population of connected vehicles in a given cell, with respect to lateral movements, is representative for the total vehicle population in that cell (for further details see, Bekiaris-Liberis et al., 2017; Papadopoulou, Roncoli, Bekiaris-Liberis, Papamichail & Papageorgiou, 2018); and the variables involved in (19) and referring to connected vehicles may be readily extracted as measurements from the connected vehicles reports.

Similarly to the case of cross-lane estimation, we can write (17)–(19) in the following form

$$x(k+1) = A(v^c(k), L^c(k), \rho^c(k))x(k) + Bu(k),$$
$$y(k) = C(v^c(k), L^c(k), \rho^c(k))x(k), \tag{20}$$

where $x = (\rho_{1,1}, \dots, \rho_{N,1}, \dots, \rho_{1,M}, \dots, \rho_{N,M}, r_{1,M}, \dots, r_{N,M}, s_{1,M}, \dots, s_{N,M})^{\mathrm{T}}$, while y and u consist of flow measurements from fixed detectors, as in Section 3.2.3.

3.2.2. Estimation scheme

For estimation of x we employ a Kalman filter using model (20) and measurements v^c, L^c, ρ^c, y, u.

3.2.3. Observability and stability

As in the cross-lane case, in order to guarantee exponential stability of the Kalman filter utilized for state estimation of system (20), the most crucial fact is to show the strong structural observability of (20) Bekiaris-Liberis et al., 2017). Under

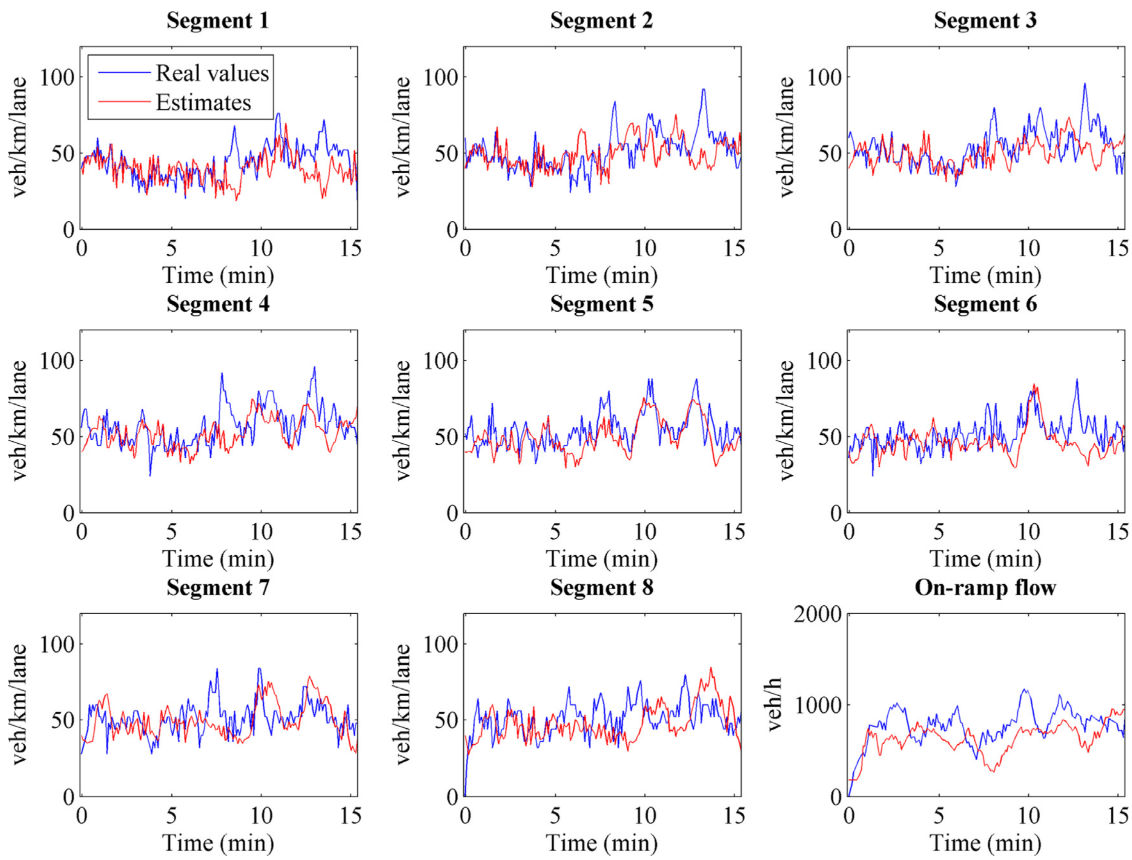

Fig. 5. Cross-lane estimation – real and estimated densities for the NGSIM case study for 5% penetration rate of connected vehicles.

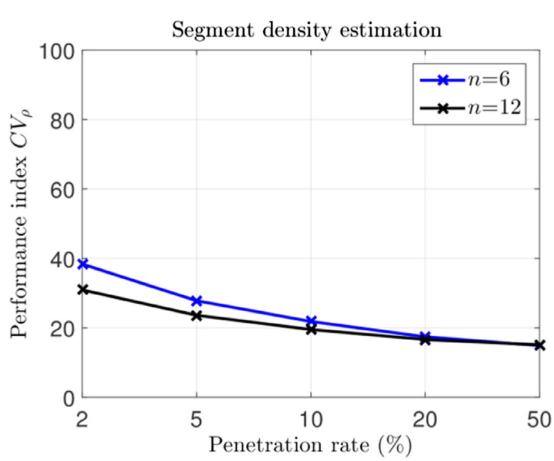

Fig. 6. Cross-lane estimation – performance indices of density estimation for various penetration rates in the microscopic simulation experiments for 6 and for 12 time steps used when calculating the moving average of speed computed from connected vehicle reports.

the assumptions that the average speeds of connected vehicles are nonzero and satisfy a modified (to account for lateral flows) Courant–Friedrichs–Lewy-type condition, system ((20) (where, for simplicity, all percentage values for diagonal lateral and on-ramp flows are set to zero) is strong- structurally observable if and only if fixed flow detectors are placed at the mainstream exit and entry in each lane of the considered stretch, as well as at every cell immediately upstream of a cell with a ramp (see Fig. 4(b)). For physical systems, weak structural observability is usually sufficient for observability, which may be guaranteed when, for each pair of unmeasured ramps, an additional fixed flow sensor is placed anywhere between them (Bekiaris-Liberis et al., 2017).

3.2.4. Case studies

Real data validation using NGSIM data: We employ again NGSIM data, now dividing the stretch in four 100-m long segments. The performance of the per-lane estimation scheme is shown in Fig. 7.

Microscopic simulation-based validation: We utilize a model of the stretch of motorway A20 from Rotterdam to Gouda, in the Netherlands, (see Fig. 2(a)) implemented and validated, as outlined in Section 2.1.2, with real, lane-specific, traffic data, thus providing a realistic ground truth scenario. The estimation results are shown in Fig. 8 and indicate good estimation results even for very low penetration rates, see, Papadopoulou et al. (2018) for details.

4. Traffic flow control

VACS give rise to new opportunities for more efficient traffic control. This is due to the increased control granularity (e.g., control by lane, control by destination, control of individual vehicles) and the arbitrary space-time resolution of control measures that one may use (instead of the fixed-location traffic signs, VMS, VSL etc.). Vehicle speed control or efficient lane assignment are just two such new opportunities where automated vehicles can be exploited as actuators to improve traffic flow. Some more examples of related developments are given in what follows.

4.1. Cooperative merging

The very first article addressing the problem of efficient merging of two single-lane streams of automated vehicles was published as early as 1969 (Athans, 1969) using the then innovative

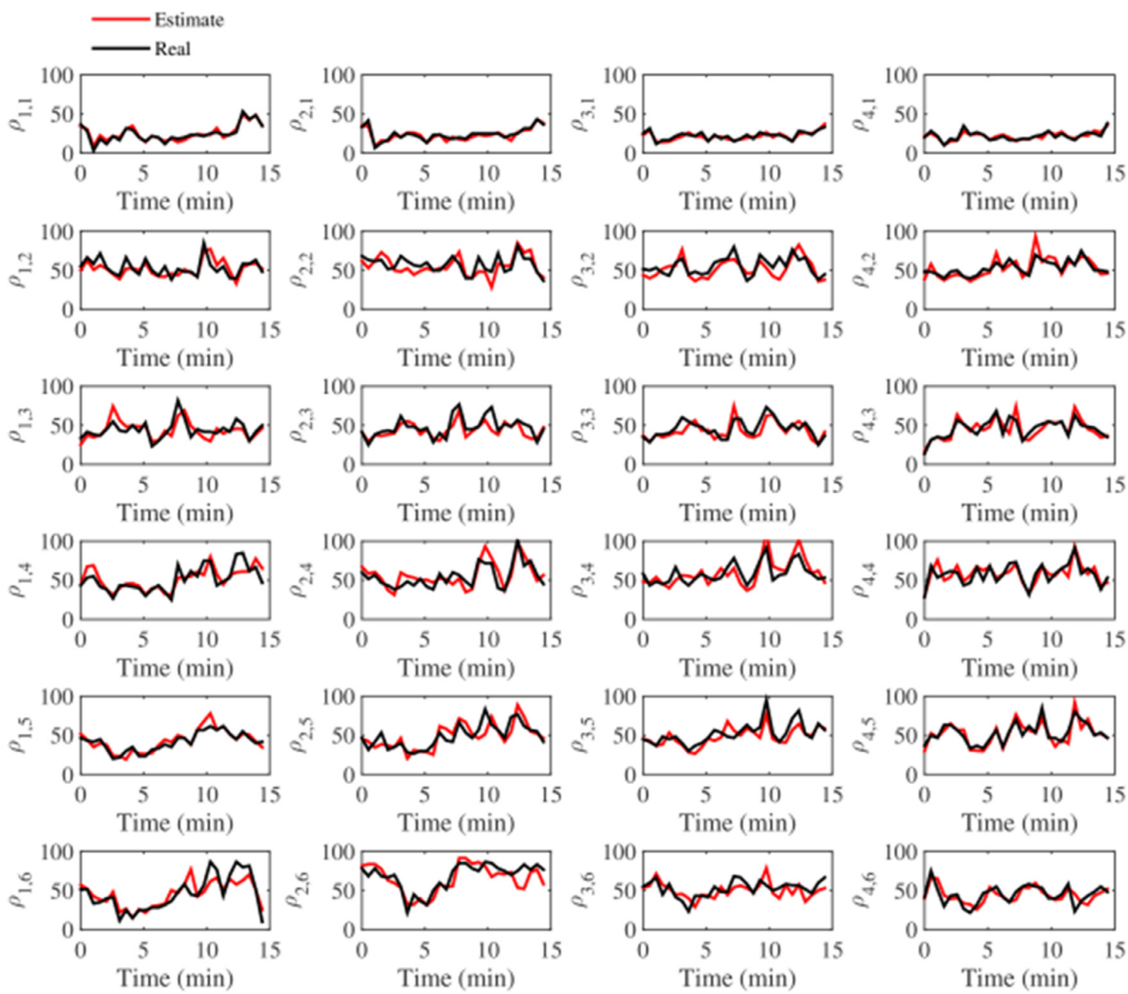

Fig. 7. Per lane estimation – real and estimated densities for the NGSIM case study for 20% penetration rate of connected vehicles.

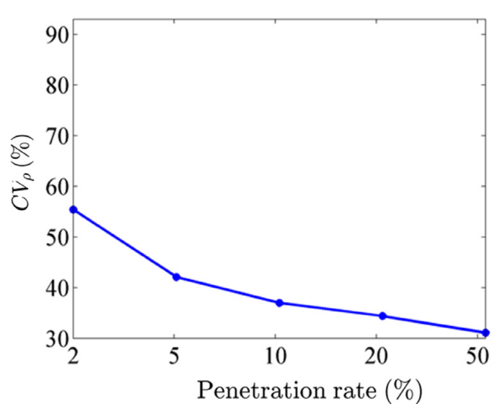

Fig. 8. Per-lane estimation – performance indices of density estimation for various penetration rates in the microscopic simulation experiments.

LQR methodology. Some few works addressing vehicle merging appeared in the following decades, but the problem gained significance and popularity in the last decade thanks to the emergence of VACS, which led to multiple, partly overlapping approaches by various groups, see, Rios-Torres and Malikopoulos (2017) and Schmidt and Posch (2010) for dedicated informative overviews of past and more recent developments. Automated vehicle merging may be viewed as a general problem in the wider transportation domain. In the particular case of motorways, merging of vehicles entering the mainstream from on-ramps is one of the major causes of congestion. Moreover, in manual driving, the merging procedure is stressful for the drivers, since it requires a synchronized set of fast observations and actions. Therefore, the development of automated procedures for equipped vehicle merging is important, as it can increase passengers' safety and convenience and alleviate congestion.

As suggested by Ntousakis, Nikolos and Papageorgiou (2016), the overall problem complexity may be mitigated by appropriate functional decomposition. A merging location point is specified on the mainstream towards the end of the on-ramp's acceleration lane. This is the point where all merging vehicles (from either the mainstream or the on-tamp) end the merging maneuvers. All vehicles located upstream of the merging point up to a certain distance (of, e.g., some 200 m), on either the mainstream or the on-ramp, belong to the merging control region and are subject to merging control. We distinguish the following functional control layers:

- The *traffic management layer* specifies the required speed and time-headway that vehicles should have when reaching the merging point. These quantities are specified, depending on the current demand, so as to maximize safety and throughput for the merged total flow. For example, for high demand, the time-headway (which is the inverse of flow) may be set corresponding to capacity; while for lower demand, there is a range of possible settings to select from according to other considerations.
- The *merging sequence layer* specifies the sequence of vehicles in the control region in reaching the merging point. There are

various ways of doing this, such as: FIFO; according to current vehicle speeds and distances; optimal. The MS is updated regularly, e.g., whenever a new vehicle enters the control region. Once a MS is specified, each vehicle obtains a putative leader, which is the vehicle to merge ahead of it. A putative leader may or may not be the physical leader (i.e., the same-lane vehicle ahead).

- The *vehicle control layer* calculates a longitudinal vehicle trajectory up to the merging point by solving a finite-horizon optimal control problem. Specifically, based on a simple model of vehicle kinematics, the trajectory problem consists in moving the vehicle from its current state to the final state, at which: final position is the merging point, final speed is the one prescribed by traffic management, and final acceleration and jerk are zero. The time horizon is fixed according to the MS, the specified time-headway and the merging time of the putative leader. A quadratic criterion leads to smooth, passenger-convenient and fuel-saving trajectories. Specifically, the minimization of acceleration is directly connected to the minimization of fuel consumption, while the minimization of jerk is connected to passenger comfort. The overall problem is readily solved analytically or via a time-variant LQR.
- The vehicle trajectory problem must be solved repeatedly (MPC approach), using updated measurements in real time, until the merging procedure is finalized. Application of MPC is necessary due to many potential disturbances or changes, such as: physical leader constraints, putative leader trajectory changes, insufficient actual trajectory tracking, MS update, final speed and headway update.

As it was demonstrated by Ntousakis, Porfyri, Nikolos and Papageorgiou (2014), even relatively simple MS schemes may produce smooth merging and efficient total merged traffic flow, although partial differences in the resulting behaviour are also observed. More specifically, Ntousakis et al. (2014) tested and compared two MS algorithms. In a first algorithm, vehicles are merging in the same sequence as they are entering the control region (FIFO). In a second algorithm, vehicles are merging in a sequence which depends on the time they need to arrive to the merging point, assuming constant (current) speed inside the control region. Both algorithms specify and update (at each time step) the MS. It was assumed that all vehicles in the network are equipped with ACC systems and are enabled with V2V communication capabilities. The microscopic simulator Aimsun was used to perform the corresponding simulations for testing and demonstration. Both algorithms provided similar results concerning the macroscopic values of total merged flow and density. However, the second algorithm is closer to real driving behaviour, since it evaluates also forward gaps and mitigates unnecessary decelerations.

4.2. Vehicle trajectory control

Fully automated vehicles could improve safety and efficiency of traffic operations by reducing accidents caused by human driver errors, improve driver and passenger comfort and, at the same time, help to reduce traffic congestion. The development of fully automated driving systems is inherently related to planning and updating a vehicle path, which should be safe, collision-free, user-acceptable, as well as efficient for the vehicle itself, but also for the emerging traffic flow. Planning such a path can be seen as a trajectory generation problem, i.e., creation of a quasi-continuous sequence of states that must be tracked by the vehicle control.

The complexity of real-world environments, avoidance of static and moving obstacles, compliance with traffic rules and consideration of human driving behaviour aspects are some of the factors that make automated vehicle trajectory control a challenging problem. More in particular, the trajectory generation process must not only be effective according to a variety of criteria, but also perform real-time adaptations to an ever-changing environment, with surrounding vehicles continuously deviating from their projected trajectories. Last not least, as the penetration rate of automated vehicles increases, their behaviour should account not only for individual criteria (selfish behaviour), but also for the efficiency of the emerging traffic flow.

Potential field methods generate a two-dimensional (road surface) field, based on the design of appropriate potential functions for obstacles, road structures, traffic regulations and the goals to be achieved. Then, a vehicle trajectory is generated by moving, at any road location towards the maximum descent direction (gradient) of the field (Wang, Wu & Li, 2015; Wolf & Burdick, 2008). Ji, Khajepour, Melek and Huang (2017) proposed a trajectory generation method along with a model-predictive path tracking controller. However, the potential field methods do not behave well in the presence of mobile obstacles, as they do not consider future path information regarding the own and other vehicles movements (Shum, Morris & Khajepour, 2015). Due to the fact that the system dynamics and the movement of other vehicles are not considered during the trajectory generation, the planned path may in some situations turn out to be non-feasible to be tracked by the vehicle (Erlien, 2015). Potential field methods are quite popular due to the intuitive problem formulation and their low computational cost (Rasekhipour, Khajepour, Chen & Litkouhi, 2017), even with complex potential functions. However, there are still open issues regarding the integration of system dynamics and constraints within such methods that were discussed some three decades ago (Koren & Borenstein, 1991).

This drawback can be alleviated by formulating the trajectory generation problem as an optimal control problem. Such approaches allow for concurrent consideration of system dynamics and anticipated obstacle movements during the trajectory generation process, thus avoiding myopic actions. For example, in Carvalho, Gao, Lefevre and Borrelli (2014), the distance between the vehicle and an obstacle is used to generate approximate linear constraints for obstacle avoidance, while in Gao, Gray, Tseng and Borrelli (2014), the obstacles are considered as ellipse-shaped constraints, in order to keep the automated vehicle robustly far from them. In the same spirit, Gao, Lin, Borrelli, Tseng and Hrovat (2010) included in the cost function factors dependent on the longitudinal distance between the automated vehicle and the obstacles, in order to generate a collision-free path. In some works, the merits of both potential field and optimal control path planning techniques are combined. Rasekhipour et al. (2017) and Wang et al. (2019) developed an MPC controller for path planning of autonomous vehicles, which avoids obstacles and observes road regulations by introducing appropriate penalty functions in the objective function of the optimal control problem.

Optimal control approaches usually map the optimal control problem to a NLP problem that can be solved using numerical NLP solvers, see for example, Gray, Ali, Gao, Hedrick & Borrelli (2012), Werling and Liccardo (2012) and Ziegler, Bender, Dang and Stiller (2014). The main drawback of this mapping is that it produces a locally optimal solution, the quality of which is very much dependent on the initial guess trajectory employed.

Another attractive alternative for solving optimal control problems is the use of DP techniques (Bertsekas, 2005). DP can be applied to a broad range of system models and allows for easy integration of system and obstacle constraints. In addition, DP techniques produce a globally optimal solution for the optimal control problem. Unfortunately, due to the curse of dimensionality (Bellman, 1954), DP techniques are restricted to small-scale problems. For this reason, they are sometimes combined with

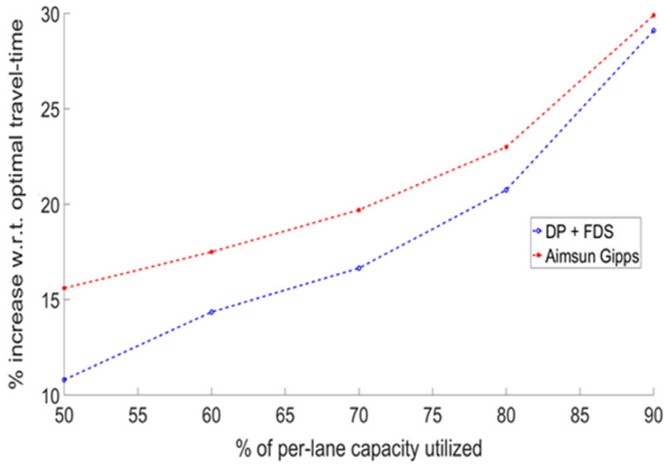

Fig. 9. In a simple highway stretch and for various traffic loads, vehicles following our path-planning approach yield a lower deviation from optimal travel time (with everyone moving at their desired speed) than conventional vehicles.

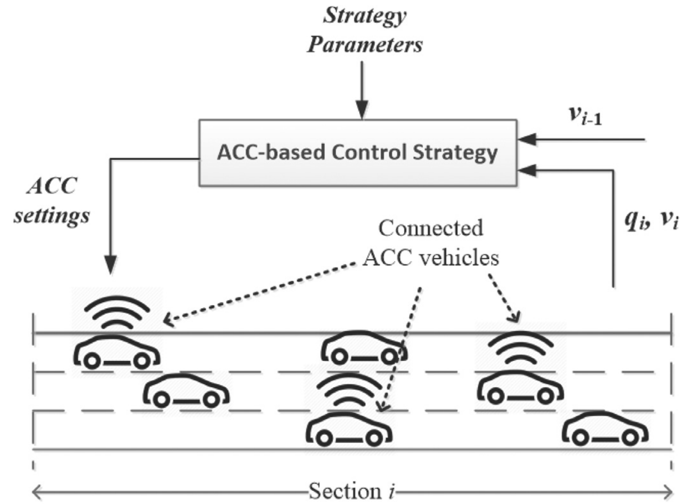

Fig. 10. Illustration of the control strategy operation.

other optimization methods. For example, Tanzmeister, Friedl, Wollherr and Buss (2013) used DP to generate a rough reference vehicle trajectory for parking scenarios, where all obstacles are considered static.

Makantasis and Papageorgiou (2018) derived an algorithm for generating a feasible path for an automated vehicle from the opportune formulation of a discrete-time optimal control problem. Vehicle dynamics form the state equations of the problem; while the road geometry, the presence of obstacles (i.e., other moving vehicles and road-boundaries) and traffic rules are taken into account via appropriate potential-field like functions to ensure path feasibility. Exploiting the structure of the system dynamics (state equations), a reduced gradient may be readily obtained, and, thereby, the optimal control problem is mapped to a NLP problem in the reduced space of the control variables. Starting from an arbitrary initial solution (or path), a local minimum is obtained with a very efficient iterative FDA (Papageorgiou, Marinaki, Typaldos & Makantasis, 2016). A simplified DP algorithm is also conceived to deliver the initial solution, greatly enhancing the quality of obtained local minima.

Based on the above work, Typaldos, Mountakis, Papageorgiou and Papamichail (2019) take advantage of low computation times to embed this optimization-based path-planning approach within a MPC framework, which is implemented in Aimsun's micro-simulation platform (TSS-Transport Simulation Systems, 2014). Considering a homogeneous motorway stretch and alongside other vehicles following Aimsun's default driving behaviour, one or more vehicles are instructed to track a path produced by the MPC-based optimization approach. The path for each such controlled vehicle is generated according to the current lane and speed of surrounding vehicles and is re-generated online in case of substantial changes. Aimsun's micro-simulation platform enables a thorough experimental evaluation of the approach, by creating a huge number of different traffic scenarios as the vehicles drive in the simulated road environment. In addition, this experimental framework allows the investigation of the impact of the suggested approach on the traffic flow as a whole for increasing penetration rates of automated vehicles. Some first results (see Fig. 9) indicate faster advancement of the ego vehicle compared to others, particularly in free-flow conditions.

Ongoing work delivers further improvements to the open-loop path-planning method by employing state-of-the-art non-convex optimization techniques, such as sequential convex programming (Lipp & Boyd, 2016), for the solution of the optimization problem. In future work, we aim for a thorough investigation of the effects of fully automated vehicles (guided in a decentralized way by our approach) on traffic flow as a function of penetration rate. In addition, it is interesting to design a common optimal control problem for the simultaneous path-planning of multiple vehicles to study the synergistic effects on overall traffic flow. Finally, we aim to design optimization objectives or weights that will not merely serve each individual automated vehicle, but also contribute to a more efficient traffic flow (e.g., focusing on mitigating congestion).

4.3. Real-time ACC time-gap control

The ACC systems have been designed to increase the driving safety and comfort. However, if conservative values are set for their parameters (e.g., the time-gap), then the ACC systems may actually lead to a deterioration rather than improvement of traffic flow efficiency, as already seen in Fig. 1. By the same token, lower than manual time-gap settings would lead to increased motorway capacity per lane and decreased capacity drop at the head of congestion, and this impact can be exploited for increased traffic flow efficiency if the settings of the ACC-vehicles could be updated dynamically in real time through the operation of an ACC-based control strategy, see, Kesting, Treiber, Schönhof and Helbing (2008).

For the design of such a control strategy (Spiliopoulou, Manolis, Vandorou & Papageorgiou, 2018), consider a motorway with both manually-driven and ACC-vehicles. The ACC-vehicle drivers may introduce their desired ACC system settings, i.e., desired speed, v_d, and minimum time-gap, T_d, but these settings are subject to change if the control strategy recommends (or orders) different values. The motorway is considered to be divided in sections, and the traffic management centre applies the proposed control strategy at every motorway section $i = 1, 2, \ldots$ independently, as illustrated in Fig. 10, in dependence of the current traffic conditions. In particular, at every control interval t_c, the strategy receives real-time measurements (or estimates) of the exiting flow q_i and mean speed v_i of every section $i$to decide on appropriate settings. The control strategy determines in real time the time-gap of the ACC vehicles that lead to increase of the static and dynamic road capacity, but this is indeed only done where and when needed. The proposed strategy has two goals which are presented below.

Capacity increase: To increase the (static) capacity, the strategy gradually decreases the suggested time- gap, when traffic flow is approaching the nominal capacity. In particular, the strategy

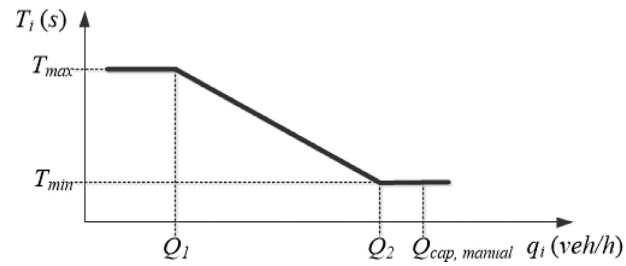

Fig. 11. Calculation of the suggested time-gap value for real-time capacity increase.

calculates the suggested time-gap as a monotonically decreasing function of the current section flow, $T[q_i(k)]$, as shown in Fig. 11. Note that the suggested time-gap value is reduced to the minimum value before the flow reaches the nominal capacity of the section. In this way, the strategy aims to delay, or even prevent, the formation of congestion, by maximizing timely the section's capacity. If, despite the capacity increase, the section becomes congested (e.g., due to even higher arriving demand or due to a shockwave arriving from downstream), then the strategy activates its second goal.

Discharge flow increase: The second goal of the proposed control strategy is the maximization of the discharge flow during congestion (dynamic capacity). It is empirically known that the discharge flow at the head of a congested area is lower than capacity, and the second goal is to mitigate this capacity drop. The strategy first identifies the location of active bottlenecks (congestion head), then suggests the minimum admissible time-gap $T_{\min}$ for all ACC vehicles in the sections just upstream and just downstream of the congestion head. In that way, the strategy achieves the increase of the discharge flow at the congestion head.

The above control decisions are summarized in the following equation which determines the suggested time-gap,

$$T_{stg,i}(k) = \begin{cases} T_i[q_i(k)] & if\ v_i(k) > v_{cong} \\ T_{\min} & at\ active\ bottlenecks \\ T_{\max} & else \end{cases} \tag{21}$$

where $k = 1, 2, \ldots$, is the discrete time index, and v_{cong} indicates the congestion limit. The control strategy decisions are calculated externally, at an infrastructure-based traffic management centre (or road-side unit) and are disseminated to the ACC-vehicles, e.g., via V2I communication. The ACC-vehicles receive the suggested time-gap, but they apply it only if their individual time-gap setting, T_d, is higher than the time-gap calculated by the controller.

The proposed strategy was tested through microscopic simulation in Aimsun using the real motorway stretch of Section 2.1.2, where congestion is created due to an on-ramp bottleneck. The simulation results showed that, the higher the penetration rate, the bigger the improvement of the traffic conditions. Figs. 12 and 13 present the spatio-temporal diagrams of speed, considering various penetration rates, for the no-control case and the strategy application case, respectively. It can be seen that, for the no-control case, the conservative ACC time-gap values lead to an increasingly strong congestion as the penetration rate of ACC-vehicles increases. On the contrary, in the control case, the control strategy achieves significant improvement even for low penetration rates (e.g., 5%), while for high penetration rates the congestion is almost resolved.

4.4. Lane-change control

4.4.1. Introduction

Lane-change control is a promising feature that can be exploited for traffic management at merging bottlenecks (e.g., lane-drops, on-ramp merges), where human drivers usually perform suboptimal lane-changes based on erroneous perceptions, which may trigger premature congestion; but even at non-merge bottlenecks (e.g., bridge, tunnel, strong curvature, grade), congestion usually starts at one lane, while other lanes still have capacity reserves, hence better lane distribution of vehicles may increase the cross-lane capacity. In the presence of a sufficient percentage of vehicles equipped with lane-changing automatic controllers or advisory systems, the overall throughput at the bottleneck location may be improved by execution of specific lane-changing commands dictated by a central decision maker.

Early works addressed the lane assignment problem for fully automated highway systems. The seminal work by Varaiya (1993) proposed a hierarchical framework for a fully automated motorway, in which the decisions on the lane-changing behaviour of vehicles are addressed in the link layer. Following this framework, several strategies have been proposed to solve the problem of lane assignment in the link layer; strategies include designing control methods suitable for real-time applications, with the development of structured heuristic rules (Rao & Varaiya, 1994); implementing lane-routing algorithms (Lee & Lee, 1997); and defining control laws to stabilize traffic conditions (Li, Horowitz, Alvarez, Frankel & Robertson, 1997). Optimization methods for path planning through lanes have also been developed, but the computation complexity of the proposed optimization problems makes them hardly applicable in a real-time context (Hall & Caliskan, 1999; Hall & Lotspeich, 1996; Kim, Cho & Medanić, 2005; Ramaswamy, Medanic, Perkins & Benekohal, 1997).

More recently, in a mixed traffic context with conventional and VACS-equipped vehicles, lane-changing control has been considered, together with variable speed limits and ramp metering, in integrated traffic management strategies (see Section 4.5). Also, a combined lane-changing and VSL control strategy was developed by Zhang and Ioannou (2017) with the purpose of avoiding lane changes in the immediate proximity of a bottleneck, which, especially in the case of heavy vehicles, may lead to premature triggering of congestion. In particular, lane-changing commands delivered as recommendations to drivers are delivered in real time according to a set of case-specific rules. Schakel and van Arem (2014) proposed a system that aims at improving traffic conditions by sending advice on lane, speed, and headway to vehicles equipped with an in-car advisory system. The advice is computed at a traffic management centre based on a lane-level traffic state prediction model. Furthermore, Guériau, Billot, Faouzi, Hassas and Armetta (2015) proposed a multi-agent decentralized framework with the aim of performing cooperative lane-changing tasks according to information exchange between vehicles and a roadside unit located in the proximity of a bottleneck.

An optimal feedback control strategy formulated as a LQR was recently proposed by Roncoli, Bekiaris-Liberis and Papageorgiou (2016a) and Roncoli, Bekiaris-Liberis and Papageorgiou (2017). The resulted linear state-feedback control law is highly efficient in real time even for large-scale networks. In contrast to other approaches, this strategy is based on a rigorous application of LQR methodology and does not involve heuristic rules. The control strategy aims at regulating the lane assignment of vehicles upstream of a bottleneck location so as to maximize the bottleneck throughput, targeting critical densities as set points.

4.4.2. Linear multi-lane traffic flow model

We consider a multi-lane motorway subdivided into segments of length L_i, where each segment is composed of $M_i - m_i + 1$ lanes (m_i and M_i being the minimum and maximum indices of lanes in segment i) indexed by j, denoting each element of the resulting grid as "cell", indexed by (i, j). The model is formulated considering the discrete time step T, indexed by $k = 0, 1, \ldots$. We

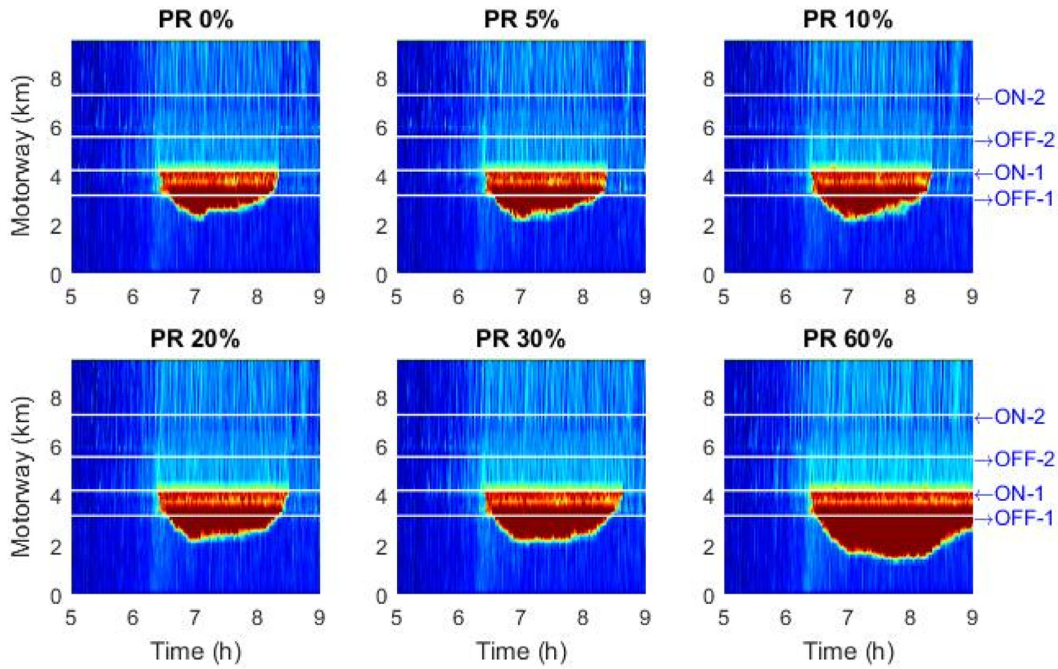

Fig. 12. No-control case: spatio-temporal diagrams of speed considering various PRs.

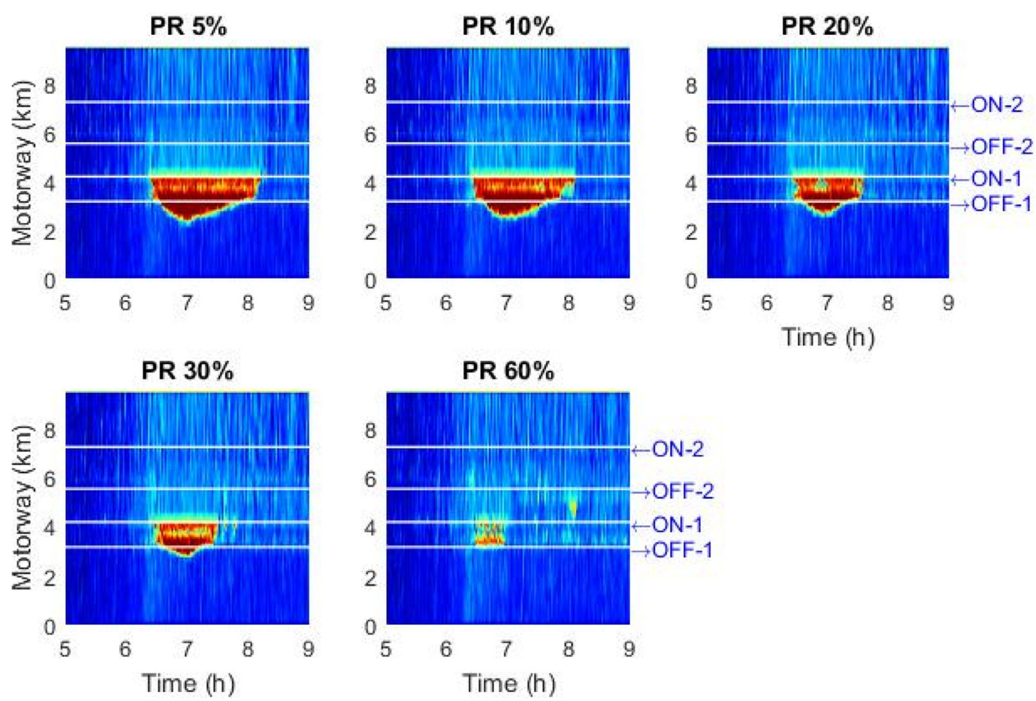

Fig. 13. Traffic control case: spatio-temporal diagrams of speed considering various PRs.

define traffic density $\rho_{i,j}$, whose dynamics evolves according to Roncoli et al. (2016a):

$$\rho_{i,j}(k+1) = \rho_{i,j}(k) + \frac{T}{L_i}\big(q_{i-1,j}(k) - q_{i,j}(k) + f_{i,j-1}(k) - f_{i,j}(k) + d_{i,j}(k)\big) \quad (22)$$

where $q_{i,j}$ is the longitudinal flow from cell (i, j) to cell $(i+1, j)$; $f_{i,j}$ is the net lateral flow from cell (i, j) to cell $(i, j+1)$ (i.e., from right to left lanes); and$d_{i,j}$ is the external flow entering the network in cell (i, j). Considering the well-known relation $q_{i,j} = \rho_{i,j}v_{i,j}$ and assuming that speeds $v_{i,j}$ are known parameters, model (22) can be seen as an LPV system in the form

$$x(k+1) = A(k)x(k) + Bu(k) + d(k), \quad (23)$$

where $x = [\rho_{0,m_0} \dots \rho_{N,M_N}]^T$, $u = [f_{0,m_0} \dots f_{N,M_N-1}]^T$, and $d = [\frac{T}{L_0}d_{0,m_0} \dots \frac{T}{L_N}d_{N,M_N}]^T$.

4.4.3. LQR problem formulation

The proposed control actions are intended for usage prior to the possible onset of congestion, aiming to delay or avoid it. Therefore, we may assume that the overall traffic flow entering the controlled area does not yet exceed the bottleneck capacity, and, hence, that the speed in all cells is high and roughly constant, which implies that (23) can be written as an LTI system

$$x(k+1) = Ax(k) + Bu(k) + d(k). \tag{24}$$

We define the following quadratic cost function, over an infinite time horizon, that accounts for the penalization of the difference between some selected densities and pre-specified (constant) set-point values, as well as a penalty term aiming at maintaining small control inputs, i.e., small lateral flows:

$$J = \sum_{k=0}^{\infty} \left\{ \left[Cx(k) - \hat{y}\right]^T Q \left[Cx(k) - \hat{y}\right] + u^T(k)\, R\, u(k) \right\}, \tag{25}$$

where $Q = Q^T \geq 0$and $R = \varphi I > 0$ are weighting matrices associated to the state tracking error and control actions, respectively, while C reflects the cells that are tracked, namely the cells at the bottleneck location for which set-points $\hat{y}$ are used.

4.4.4. Stabilizability, detectability, and regulator

The problem of minimizing (25) subject to (24) can be solved through an LQR, which provides a stabilizing feedback control law if the original system is, at least, stabilizable and detectable (Lewis, Vrabie & Syrmos, 2012). Since eigenvalues λ of matrix A are equal to the elements in the main diagonal (A is, by construction, lower triangular) and v is always positive, the only marginally stable modes are the ones related to segments without any other segment downstream (i.e., at a lane-drop). Applying the Hautus-test (Lewis et al., 2012) to marginally stable modes for the pair (A, B), we see that stabilizability is trivially satisfied for any system following the defined network structure. On the other hand, testing the pair (A, C) for detectability results in the requirement for an arbitrary set-point also for cells that do not have any other cell downstream.

The solution to the proposed LQR problem is the linear feedback/feedforward control law

$$u^* = -Kx + u_{\text{ff}}, \tag{26}$$

$$u_{\text{ff}} = \left(R + B^T P B\right)^{-1} B^T (I - (A - BK)^T)^{-1} \left(C^T Q \hat{y} - Pd\right), \tag{27}$$

where the feedback gain matrix K is defined according to classic LQR theory and can be computed offline by using the solution P of the Algebraic Riccati Equation Williams & Lawrence, 2007). Note that in the LQR derivation we assumed that the external flows d are constant, but ((27), which is an affine function of d, may be computed online for (slowly) time-varying inflows.

4.4.5. Optimal set-point tuning via extremum seeking

The set-points $\hat{y}$ should typically be set equal to the critical density values (for each lane), at which the flows are maximum. If these values are not known reliably at the bottleneck location, one may employ discrete-time extremum seeking (Anderson & Moore, 1971) for tuning set-points, aiming at achieving an optimal value of a cost (flow maximization) utilizing only real-time measurements. We use as a cost function TTT over a finite time horizon K, as defined by Ariyur and Krstić (2003). Experimental results show a fast convergence to the optimum TTT, corresponding to set-points equal to critical densities, as can be seen in Fig. 14.

4.4.6. Policy-based density distribution at bottlenecks

As a result of implementing the control law 26) and (27), the traffic density distribution among different lanes remains (roughly) constant under any demand scenario. Although this behaviour would not produce any negative impact on the traffic performance, it may be, in some circumstances, undesirable to road traffic authorities, who may, for various reasons (e.g., because of lane usage regulations), prefer different specific lane distributions for different flow demand. In such cases, the control law

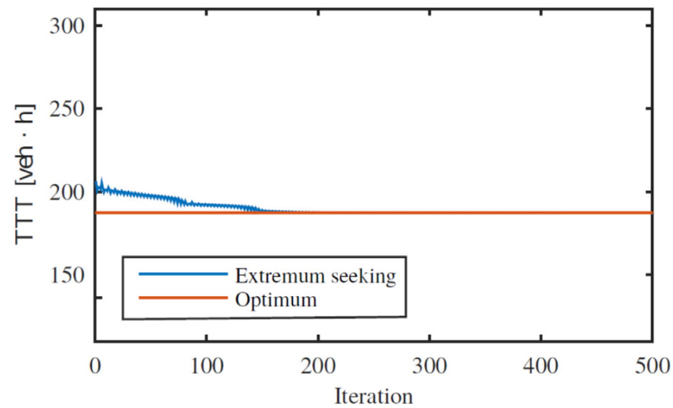

Fig. 14. Cost function value achieved by applying the extremum seeking algorithm.

may be switched on only when the flow approaches capacity and congestion seems imminent. Alternatively, one may extend the control strategy so that, besides aiming at tracking the critical density (e.g., when demand is close to bottleneck capacity), it also aims at distributing the vehicles in the bottleneck area among the different lanes according to a given policy. This is achieved by modifying the feed-forward term of control law ((27) as follows

$$u_{\text{ff}}(k) = \left(R + B^T P B\right)^{-1} B^T (I - (A - BK)^T)^{-1} \left(C^T Q\, \psi(d(k)) - P\, d(k)\right), \tag{28}$$

where the function ψ defines the pursued lane distribution policy.

The reported results (Fig. 15 and Fig. 16) were obtained by use of macroscopic simulation, whereby the controller decisions are directly applied to the simulator as macroscopic lateral flows. For practical applicability of the method, the macroscopic lateral flows need to be converted to individual messages to be submitted to a corresponding number of connected vehicles, something that does not create any major methodological difficulties. In fact, such a realization was developed by Markantonakis, Skoufoulas, Papamichail and Papageorgiou (2019), where the lane-change control method was combined with mainstream flow control (implemented by use of vehicle speed control) and was tested in microscopic simulation.

4.5. Integrated motorway network control

As discussed, the use of VACS permits the implementation of an increased range of control tasks, including vehicle-actuated variable speed limits and lane-changing control, which produce unprecedented capabilities for link-level motorway control. We present here a model-based control approach, which addresses simultaneously, in an integrated way, multiple control measures for a whole motorway link or network through the formulation of a linearly-constrained convex QP problem, based on a first-order multi-lane model that has been appropriately designed (see Section 2.2.2).

4.5.1. Optimal control problem formulation

We subdivide a given motorway stretch into segments $i = 1, \ldots, I$ and lanes $j = 1, \ldots, J$, while considering a discrete time index $k = 1, \ldots, K$, where$K$ is the optimization horizon. We manipulate the following three control actions, where each action ω has a different index k^{ω}reflecting different control steps:

- RM, described by $r_{i,j}(k^R)$, that represents the inflow from the on-ramps to the motorway mainstream.
- MTFC, described by $q_{i,j}(k^Q)$, that represents the mainstream flow from a cell to the downstream one, which could be implemented via variable speed limits.

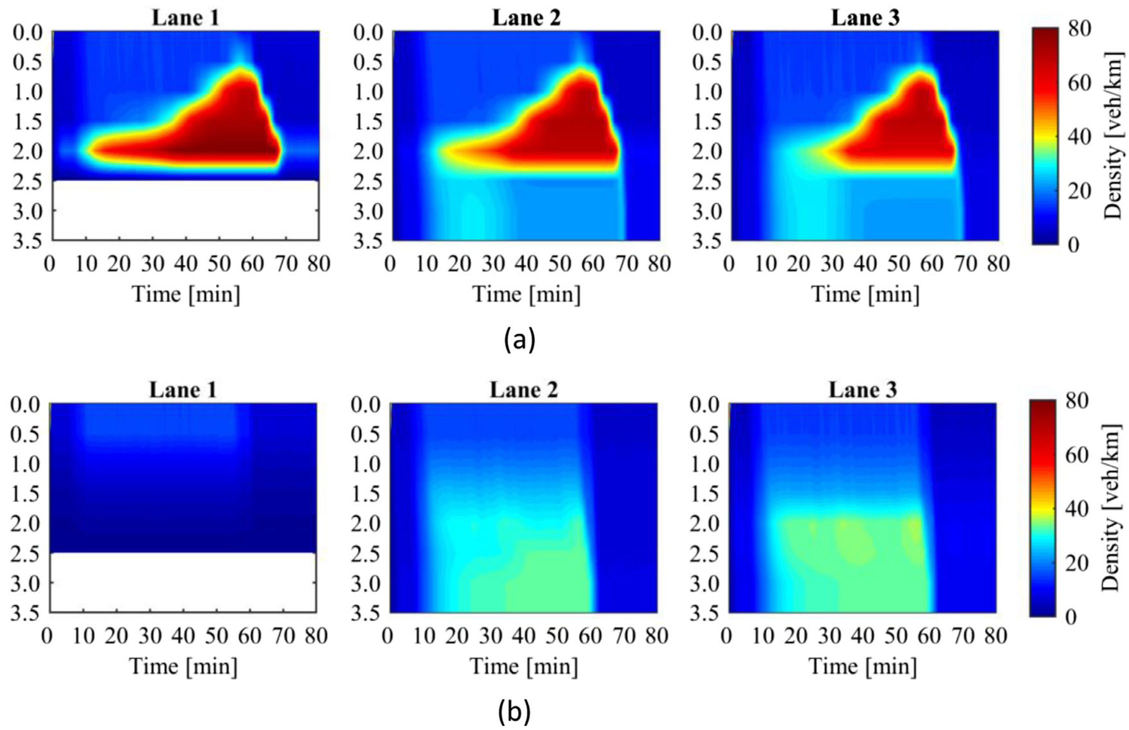

Fig. 15. Density contour plots for: (a) the no-control case; and (b) the control case applying strategy 26) and ((27) with constant set-points.

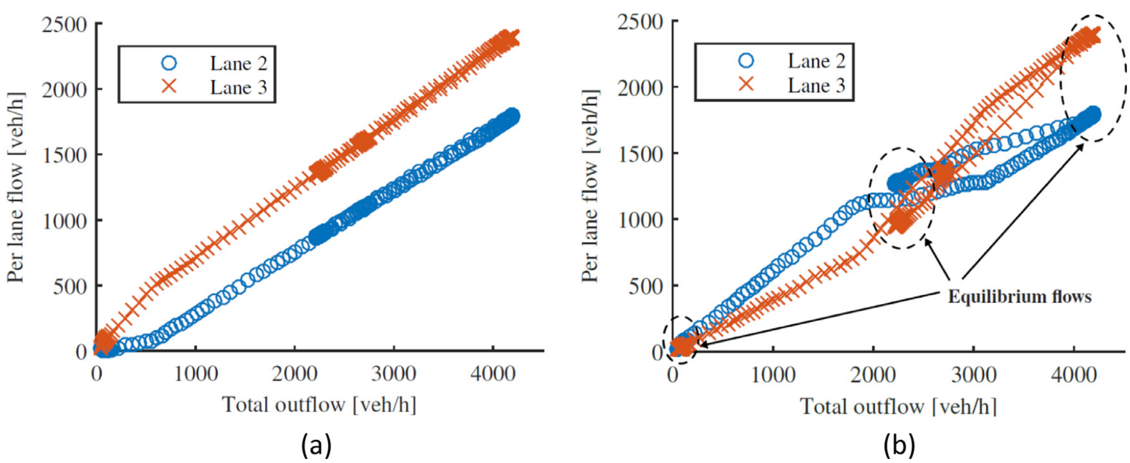

Fig. 16. The flow exiting the bottleneck area for the feedback control strategy: (a) with constant set-points; and (b) for policy-based density distribution.

- LCC to define ordered lateral flows for each segment-lane, enabling an optimal distribution of traffic flow among the different lanes; the corresponding control variables are $f_{i,j,\bar{j}}(k^F)$, denoting the flow of vehicles moving from lane j to lane $\bar{j}$ ($\bar{j} = j \pm 1$) of segment i.

The dynamic equation for densities $\rho_{i,\,j}$ is given by the following conservation equation:

$$\rho_{i,j}(k+1) = \rho_{i,j}(k) + \frac{T}{L_i}\Big[q_{i-1,j}(k^Q) + r_{i,j}(k^R) - q_{i,j}(k^Q) - \gamma_{i,j}(k)\sum_{j=1}^{J} q_{i-1,j}(k^Q) + f_{i,j+1,j}(k^F) + f_{i,j-1,j}(k^F) - f_{i,j,j-1}(k^F) - f_{i,j,j+1}(k^F)\Big] \quad (29)$$

where $\gamma_{i,\,j}(k)$ are estimated turning rates at off-ramps. RM actions may lead to the creation of queues at on-ramps $w_{i,\,j}(k)$, modelled by the following dynamics, where $d_{i,\,j}(k)$ is the external demand feeding the ramp queue

$$w_{i,j}(k+1) = w_{i,j}(k) + T\big[d_{i,j}(k) - r_{i,j}(k^R)\big]. \quad (30)$$

Longitudinal flows are modelled via a piecewise-linear FD, with an additional linear function to reflect the capacity drop phenomenon if the upstream density is over-critical (Roncoli et al., 2015b), although alternative approaches may be employed, as shown in Kontorinaki et al. (2017), see Section 2.2.2. Since longitudinal flows are assumed controllable via corresponding lowering of equipped vehicle speeds, the FD is converted to upper bounds for the controllable longitudinal flows as follows.

$$q_{i,j}(k) \le v_{i,j}^{free}\rho_{i,j}(k), \quad (31)$$

$$q_{i,j}(k) \le -\frac{v_{i,j}^{free}\rho_{i,j}^{cr} - q_{i,j}^{jam}}{\rho_{i,j}^{jam} - \rho_{i,j}^{cr}}\rho_{i,j}(k) + \frac{\rho_{i,j}^{cr}\left(v_{i,j}^{free}\rho_{i,j}^{jam} - q_{i,j}^{jam}\right)}{\rho_{i,j}^{jam} - \rho_{i,j}^{cr}}, \quad (32)$$

$$q_{i,j}(k) \le v_{i+1,j}^{free}\rho_{i+1,j}^{cr}, \quad (33)$$

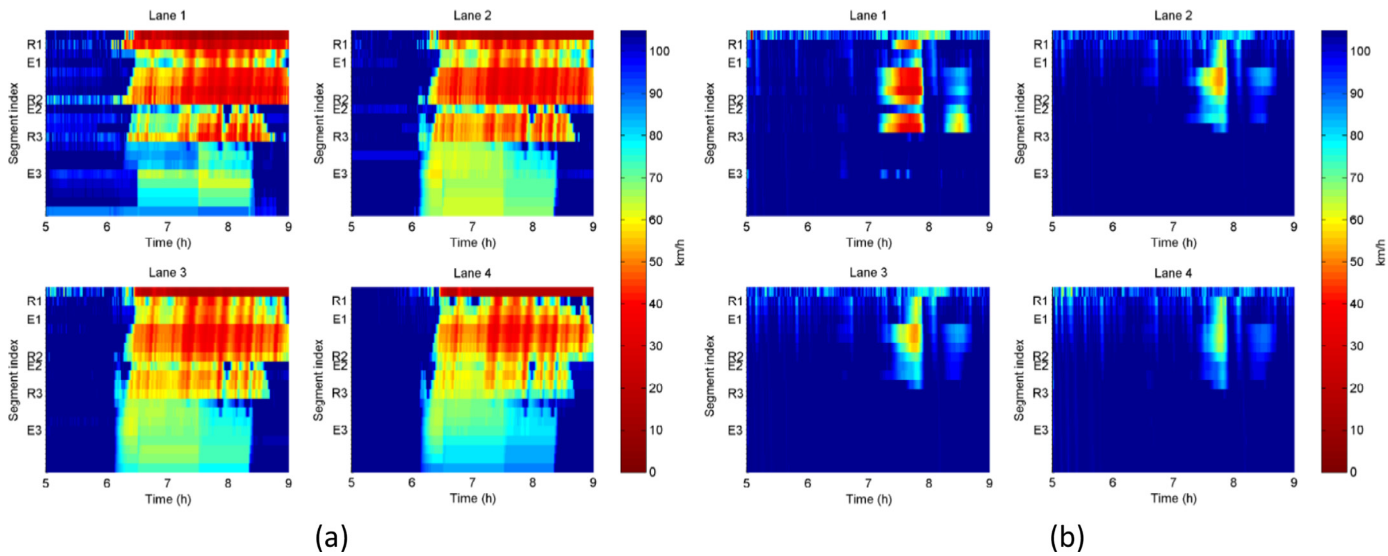

Fig. 17. Speed contour plots: (a) for the no-control case; and (b) the optimized case; of case study 1 for on-ramp demand increased by 30%.

$$q_{i,j}(k) \leq -\frac{v^{free}_{i+1,j}\rho^{cr}_{i+1,j}}{\rho^{jam}_{i+1,j} - \rho^{cr}_{i+1,j}}\rho_{i+1,j}(k) + \frac{v^{free}_{i+1,j}\rho^{cr}_{i+1,j}\rho^{jam}_{i+1,j}}{\rho^{jam}_{i+1,j} - \rho^{cr}_{i+1,j}}, \tag{34}$$

where $v^{free}_{i,j}$ is the free-flow speed, $\rho^{cr}_{i,j}$ is the critical density, $\rho^{jam}_{i,j}$ is the maximum admissible density, and $q^{jam}_{i,j}$ is the minimum flow achievable due to the capacity drop.

The computation of lateral flows is fully delegated to the optimizer, while only upper bounds are specified to the non-negative lateral flows as follows:

$$\left[f_{i,j,j-1}(k^F) + f_{i,j,j+1}(k^F)\right] \leq \frac{L_i}{T}\rho_{i,j}(k), \tag{35}$$

$$\left[f_{i,j-1,j}(k^F) + f_{i,j+1,j}(k^F)\right] \leq \frac{L_i}{T}\left[\rho^{jam}_{i,j} - \rho_{i,j}(k)\right], \tag{36}$$

$$f_{i,j,j-1}(k^F) \leq f^{\max}, \tag{37}$$

$$f_{i,j,j+1}(k^F) \leq f^{\max}. \tag{38}$$

Finally, we employ a quadratic cost function that includes (Roncoli, Papageorgiou & Papamichail, 2015c).

- Linear terms reflecting TTS, as the most crucial control objective, which includes both the total travel time on the mainstream and the total waiting time at on-ramp queues, and a penalty term to avoid excessive lateral (lane-changing) flows at specific locations.
- Quadratic penalty terms to reduce time variations of RM and LCC control variables, as well as to reduce time and space fluctuations of the speed values (approximated via appropriate linearized expressions).
- The resulting optimization problem has a convex QP form, which allows achieving a global optimum (in contrast to other nonlinear approaches) in very low computation time also for large-scale systems.

4.5.2. Case study 1: open-loop optimization

We implement our optimization problem for a 4-lane network stretch of 5.26 km in length, which includes three on-ramps and three off-ramps, of the Monash Freeway (M1) around Melbourne, Australia. We investigate the morning peak period (5 a.m.–9 a.m.), where a major congestion appears due to high demand and weaving close to the ramps. First, the model parameters of the multi-lane traffic flow model were calibrated by use of real traffic data (Roncoli et al., 2015b) (no-control case); then, the optimization problem, with tuned parameters was applied for the entire 4-hour horizon. We observe that the TTS improves by 23% with respect to the no-control case, employing only RM and LCC actions. In addition, we test a scenario where the on-ramp demands are increased by 30% and the resulting optimization shows a 52% improvement of TTS with respect to the corresponding no-control case (see Fig. 17), with the use of all three control actions; see, Roncoli, Papageorgiou and Papamichail (2015a) for more details.

4.5.3. Case study 2: model predictive control in microscopic simulation

We perform further experiments in an MPC framework using the microscopic traffic simulator Aimsun, with opportunely modified car-following and lane-changing models. We implemented the model of a stretch of motorway A20 from Rotterdam to Gouda in the Netherlands, validated with real traffic data (as discussed in Section 2.1.2) featuring a daily congestion pattern (see Fig. 18, top). The stretch contains all ingredients of a complex infrastructure (lane-drop, on- and off-ramps). We implement appropriate algorithms to translate optimal flows to speed or lane-changing commands. Results show the capability of the proposed method to improve traffic conditions, via flexible coordination of all available control actions (see Fig. 18, middle), as well as when excluding RM from the set of control actions (see Fig. 18, bottom). In addition, in Roncoli, Papamichail and Papageorgiou (2015), we evaluate a scenario where different percentages of vehicles are equipped with ACC systems, showing that the detrimental effects due to the choice of a high headway in ACC systems (capacity reduction) may be mitigated by using an appropriate control strategy acting at a macroscopic level.

4.6. Other developments

Further interesting developments of vehicle-based traffic control, beyond those addressed in previous sections, concern the design of eco-driving vehicle trajectories (Typaldos, Papamichail & Papageorgiou, 2018) and of string-stable ACC control laws (Bekiaris-Liberis, Roncoli & Papageorgiou, 2018).

Another stream of work extends and applies recent advanced nonlinear feedback concepts to a variety of motorway traffic control problems. A number of related significant and rigorous results are of significance for both conventional and VACS-

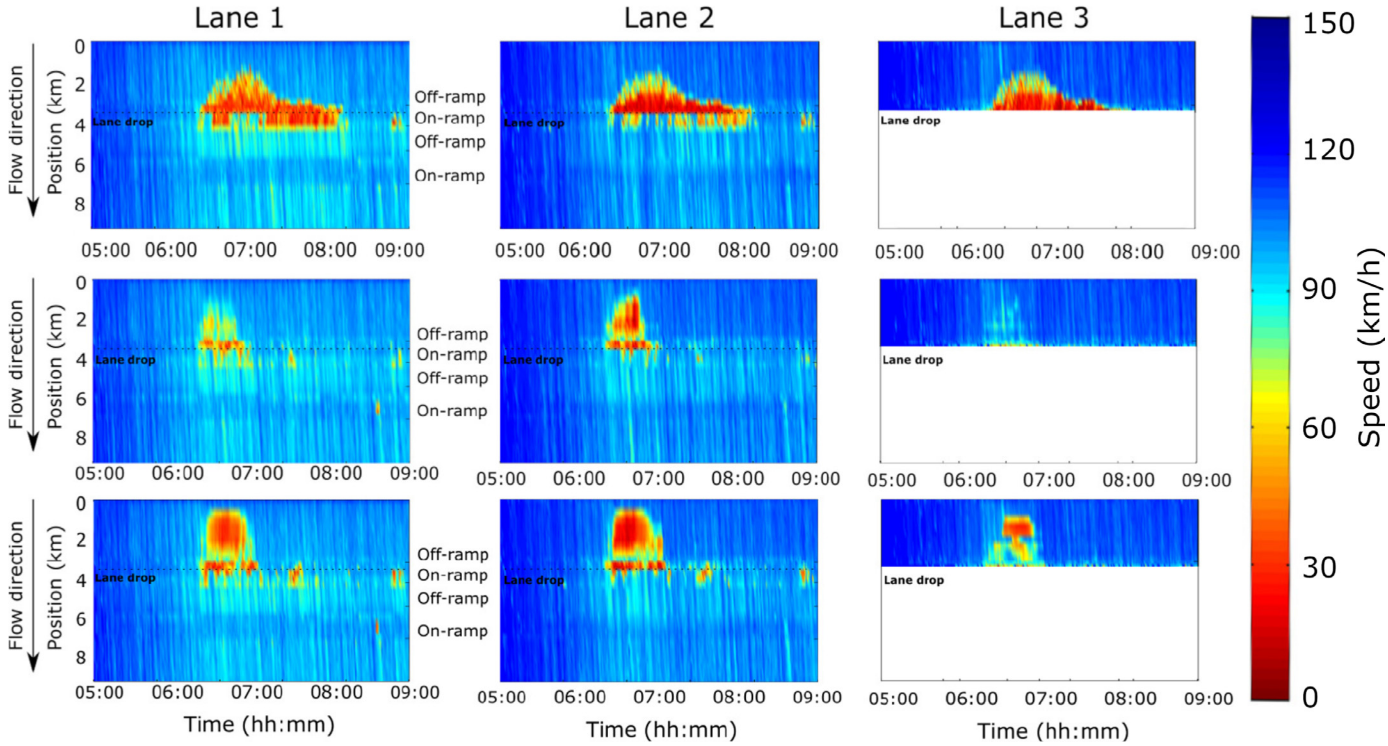

Fig. 18. Contour plots of the speed in the no-control case (top), applying MPC considering all control actions for 50% penetration rate (middle), and applying MPC without RM (bottom) in case study 2.

including traffic flow (Karafyllis, Kontorinaki & Papageorgiou, 2017; Kontorinaki, Karafyllis & Papageorgiou, 2019). This work stream may indeed attract more researchers to adopt the proposed paradigm for nonlinear feedback traffic control. Finally, motorway traffic control with novel PDE-based approaches delivered preliminary, but promising results (Karafyllis & Papageorgiou, 2019; Karafyllis, Bekiaris-Liberis & Papageorgiou, 2018).

5. Conclusions

The emergence of novel technologies pertaining to vehicle automation and connectivity at various levels bears some risks with regard to their impact on the emerging traffic flow efficiency; but also offers unprecedented opportunities for safer and more efficient traffic flow. The latter is conditioned by the development of appropriate traffic management concepts that exploit the available and forthcoming novel features in a multitude of ways. This paper presented an overview of developments and needs regarding motorway traffic management in presence of VACS, with particular focus on achievements obtained within TRAMAN21.

TRAMAN21 was the first ERC Advanced project to address traffic management and produced a number of innovative concepts, tools and results that open up new horizons for traffic management research and practice in presence of VACS. In a first step, one needs to gain awareness about the opportunities offered by novel vehicle technologies, hence an extensive review established the set of VACS features, which are most relevant from a motorway traffic management perspective. Traffic flow modelling in presence of VACS is a prerequisite for the design and testing of efficient traffic management approaches and must be addressed at two levels, microscopic and macroscopic, for a variety of utilizations. A microscopic simulator in presence of VACS was outlined as an add-on of a commercial conventional simulator by appropriately modifying the vehicle behaviour to reflect the impact of selected VACS. At the macroscopic level, novel macroscopic traffic flow models were presented, able to capture multi-lane highway traffic as well as traffic comprising VACS-equipped vehicles at arbitrary penetration levels.

In the evolving traffic environment with VACS, equipped vehicles may act as moving sensors as well as actuators, exhibiting a driving behaviour that improves the emerging traffic flow and executing orders and advice received from the traffic control centre so as to maximize network efficiency and minimize congestion. To this end, innovative traffic estimation and control methods and tools were presented and tested in simulation. In particular, traffic control was addressed at vehicle level, local level and network level and comprises unconventional actions that are not feasible by use of the current road-side actuator technology.

It is worth mentioning at this point that, in the frame of the EU H2020 project INFRAMIX (www.inframix.eu), the presented estimation tools and some of the control methods described in this paper are being tested in real traffic conditions.

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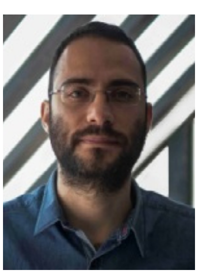

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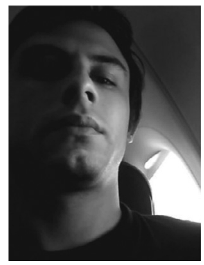

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