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Towards Connected Autonomous Driving: Review of Use-Cases

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Connected autonomous vehicles are considered as mitigators of issues such as traffic congestion, road safety, inefficient fuel consumption, and pollutant emissions that current road transportation system suffers from. Connected Autonomous vehicles utilise communication systems to enhance the performance of autonomous vehicles and consequently improve transportation by enabling cooperative functionalities, namely, cooperative sensing and cooperative manoeuvring. The former refers to the ability to share and fuse information gathered from vehicle sensors and road infrastructures to create a better understanding of the surrounding environment while the latter enables groups of vehicles to drive in a co-ordinated way which ultimately results in a safer and more efficient driving environment. However, there is a gap in understanding how and to what extent connectivity can contribute in improving the efficiency, safety and performance of autonomous vehicles. Therefore, the aim of this paper is to investigate the potential benefits that can be achieved from connected autonomous vehicles through analysing five use-cases: (i) vehicle platooning, (ii) lane changing, (iii) intersection management, (iv) intersection management, and (v) road friction estimation. The current paper highlights that although connectivity can enhance the performance of autonomous vehicles and contribute to improvement of current transportation system performance, the level of achievable benefits depends on factors such as the penetration rate of connected vehicles, the number of autonomous vehicles, traffic scenarios, and the way of augmenting off-board information into vehicle control systems.

Keywords: Connected Autonomous Vehicles, cooperative driving, use-case analysis

1. Introduction

Road safety, ineffective use of the roadway infrastructure, inefficient fuel consumption and pollutant emissions are the main challenges associated with the current transportation system [1]. In terms of road safety, it is noted that about 92% of the road crashes are mainly caused by human recognition errors (e.g. drivers inattention, drivers distractions, and inadequate surveillance) and human decision errors (e.g. driving too fast, false assumption of others actions, and misjudgement of gap or others speed) [2, 3]. Also, it is remarked that erroneous drivers decisions are not only responsible for road fatalities but also for the underuse of road infrastructure and excessive fuel consumption. For instance, it was shown in [4] that erroneous driving styles which include excessive

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acceleration/braking and engine idling have a notable negative impact on fuel consumption (e.g. an increase of about 3-5 litres per 100km) and emission pollutions. Also, it has been noted that current road infrastructures are not operated at their maximum capacity by human driven vehicles and only 11% of the road lane length of highways are occupied by vehicles while the remaining 89% represents the gaps that the drivers need to maintain behind other vehicles in order to feel safe while driving at high speed [1]. Connected Autonomous Vehicles (CAVs) which benefit from autonomous vehicle and connected vehicle technologies are considered as a potential mitigator of current transportation system challenges. It is noted that an autonomous vehicle is able to perceive its environment, and use control systems to autonomously plan vehicle motion and decide vehicle manipulation commands. Autonomous vehicles can improve road safety through precise control of the position and velocity (e.g. tight control of inter-vehicular distances) and smaller reaction time compared with human driven vehicles [1]. Furthermore, they can operate the engine and vehicle powertrain in regions with high efficiency resulting in a reduction of fuel consumption and pollutant emissions. However, the performance of non-connected autonomous vehicles in different manoeuvring scenarios and traffic conditions are restricted due to limitation of on-board sensing systems (e.g. direct line of sight, sensor accuracy in wide range of environment conditions, sensor operation range, etc.). On the other hand, connected vehicles refer to those vehicles which are capable of exchanging information with other vehicles or roadside infrastructures by using wireless communication technologies [5]. Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication technologies enable vehicles to access external information that cannot be directly obtained through on-board vehicle sensing systems (e.g. the position of vehicles beyond the line of sight, traffic data ahead, and roadway conditions). This external information can be fused with on-board observation to create a better perception of the surrounding environment. It is reported in [6, 7] that equipping autonomous vehicles with communication systems significantly enhance their performance and consequently the efficiency of transportation systems. Also, it enables cooperative manoeuvring which is the ability to jointly plan trajectories and decisions so that a common goal for the fleet, e.g. minimisation of fuel consumption while preserving safety, can be achieved [8]. It is noted that cooperative manoeuvring is not possible neither with the sole use of connected vehicles nor with autonomous vehicles but it is a feature that emerges when connectivity is added to autonomous vehicles. The potential of a Vehicle-to-Everything (V2X) platform in expanding the capabilities of autonomous vehicles was initially investigated through European research projects such as Cybercars-2 [9], SARTRE [10], and AutoNet2030 [11], just to name a few. The project Cybercars-2 (2006-2009) focused on the design, development, prototyping, and on-road testing of cooperative driving manoeuvres, such as overtaking, and crossing intersections not operated by traffic lights [9]. The results showed that in a cooperative driving environment, safety can be guaranteed while performing potentially hazardous manoeuvres such as overtaking a stationary obstacle in a single carriageway. The SARTRE project (2009-2012) focused on developing strategies to operate vehicle platoons on normal public highways with the aim to improve fuel efficiency, safety, and reduce congestion. Results from the project showed that fuel savings (potentially up to 20%) can be achieved as a result of cooperative platooning. The AutoNet2030 (2013-2016) project studied how connected autonomous vehicles can negotiate manoeuvres and interact with manually driven vehicles in a safe and reliable way by two demonstrations [11], i.e. (i) vehicle platooning in mixed traffic and (ii) vehicle cooperation in low speed driving scenarios (i.e. car following, merging, lane changing, and intersections). Currently there are research projects in the UK which aim to further investigate the use of V2X for autonomous vehicles. For instance, the target of the project UKCITE

(2016-18) is to create an environment for real-time testing of connected autonomous vehicles [12]. It involves equipping over 40 miles of urban roads, dual-carriageways and motorways within Coventry and Warwickshire with V2X technologies. The i-MOTORS project (2016 - 2018) is devoted to developing a vehicular cloud computing platform that fuses data from vehicles with information from the road environment to create dynamic maps and real-time alerts of possible roadway hazards [13]. Expected benefits from the i-MOTORS project are twofold, (i) reduction in fuel consumption and travel time by considering real time traffic data for active route planning, and (ii) improvement in road safety via car platooning. The G-ACTIVE project (2016 - 2019) targets a reduction of fuel consumption for passenger and light duty road vehicles for a range of drivetrain architectures (conventional, electric and hybrid electric) by leveraging off-board data including traffic condition and timing of traffic lights [14]. This off-board information will be used to simultaneously optimize drivetrain energy and vehicle driving speed. The aim of the CARMA project (2016-2021) is to develop and test a cooperative automated driving technology based on a distributed control system enabled by an ultra-low latency and highly reliable cloud-based infrastructure [15]. Although there are several past and on-going research activities in the domain of CAV technology, the potentials and limitations of this technology in addressing the issues of current transportation system is not well investigated [16]. Therefore, this paper is devoted to analysing achievable benefits of exploiting off-board data gathered via V2X communications, and inter-vehicular cooperation on autonomous vehicles. To investigate the potentials and limitations of CAVs, a set of five use-cases is chosen and analysed through the results presented in the current technical literature. The first four use cases (i.e. vehicle platooning, lane change, intersection management and energy management) have been selected to show examples of how connectivity can support cooperative manoeuvring thereby improving road transportation whereas the last use-case (i.e. cooperative road friction estimation) is dedicated to demonstrating how perception of the surrounding environment can be improved when vehicles cooperatively share their local perception knowledge. The analysis of cooperative localisation systems has been performed in a separate work by the authors and is reported in [17].

The remainder of the paper is organised as follow. Section 2 and Section 3 investigate the benefits of cooperative driving in highway scenarios. Section 2 is devoted to the analysis of vehicle platooning while Section 3 examines lane change manoeuvres supported by communication systems. Intersection management is analysed in Section 4 to study achievable benefits through V2X communication systems in urban environments. In Section 5 it is discussed how off-board information gathered via communication systems can be used to reduce energy consumption. Cooperative estimation of the road friction for supporting on-board safety systems of CAVs is analysed in Section 6. Finally, conclusions are drawn in Section 7.

2. Vehicle Platooning

A vehicle platoon is a group of two or more consecutive automated vehicles, also denoted as a string of vehicles, traveling along a highway in the same lane with a short inter-vehicle distance and at the same velocity. Typically, spacing strategy (also denoted as spacing policy) has been used to define the required inter-vehicular distance, while the target speed is decided by either a lead vehicle (the first vehicle in the string which can be either an autonomous or human driven vehicle) or, if available, by the road infrastructure which acts as a virtual leader [18]. There are several benefits of organising the road

vehicles in platoons, for instance (i) increasing traffic flow while reducing traffic shock waves, (ii) reducing fuel consumption and pollutant emissions, and (iii) improving road safety. Vehicle platooning also improves drivers comfort through (i) providing drivers the opportunity to focus on other activities during the trip, and (ii) generating smooth speed variations resulting in having less jerk compared with vehicles under human control. It is noted that the key parameters for increasing traffic flow through platooning are the inter-vehicular distance and the number of vehicle participating in the platoon (i.e., platoon length). The traffic flow increases when the inter-vehicular gap reduces or the number of the vehicles in a string increases. In the case that all vehicles of a highway are organised in sets of platoons, it is possible to increase traffic flow about four times and reach a value up to 8000 vehicle/hour/lane for automated highways [19]. However, in a mixed traffic scenario, the achievable traffic flow and reduction of shock waves increase as the fraction of vehicles grouped in platoons increases [20, 21]. Shortening the inter-vehicular distances also results in a reduction of fuel consumption of the platoon due to the reduction of aerodynamic drag force acting on each vehicle in the fleet. As documented by the earliest outcome of the PATH program [22, 23] the aerodynamic drag force experienced by platoons reduces when the inter-vehicular gap reduces or the number of vehicles in the platoon increases. Furthermore, the average reduction in the drag force approaches a limit as the number of platoon members increase and this limit is a function of inter-vehicular spacing. The reduction of aerodynamic drag force results into the reduction of required drive torque and therefore less fuel consumption, which is expected to be on average 20% for the inter-vehicular gap of 0.2 vehicle length (about 1 meter). Similar conclusion regarding fuel efficiency of vehicles operating in platoons have also been drawn more recently in [24, 25]. It is noted that, as human driver reaction time (of about 0.25 s) is too large to guarantee collision avoidance while driving with such reduced inter-vehicular distances, high vehicle automation is required to implement platoon scenarios [26] which also improve road safety through tight control of the inter-vehicular gap and speed [27]. However, it is worth mentioning that excessive shortening of inter-vehicular distance can have a negative impact on the passengers comfort [28]. Platoons of autonomous vehicles must guarantee two stability criteria: (i) individual vehicle stability and (ii) string stability. Individual stability requires that the difference between the reference inter-vehicular gap and the actual one (spacing error) converges to zero when the lead vehicle has a constant speed [29, 30]. The convergence speed of the spacing error to zero, known as “stability margin” is used as an index to evaluate the performance of the platoon in establishing the required cooperative motion [31, 32]. String stability refers to the stability of all vehicles traveling together in the platoon and needs to be robust against perturbations of motion of the lead vehicle [33]. Unstable strings of vehicles can induce traffic waves which force the following vehicles into sudden accelerations/decelerations, slowdown or standstill, thus reducing traffic flow and drivers comfort, while increasing at the same time fuel consumption [34] and the possibility of rear-end collisions [35]. It is noted that autonomous vehicles that adjust the inter-vehicular distance based only on the position of the lead vehicle (measured through local sensors) have limited capability to be operated in platoons [35, 36]. Furthermore, the limitation of autonomous vehicles to be organised in platoons depends also on the platoon spacing strategies. In the context of vehicle platooning, spacing strategies are mainly classified as: (i) constant policy, and (ii) headway policy (also known as velocity-dependent spacing policy). When a constant policy is adopted, the inter-vehicular gap is independent from the velocities of the vehicles. This policy can increase throughput more than the headway policy, and has been used initially to show the benefits of automated highways to increase road capacity [25]. On the other hand, in the headway policy, each



Figure 1. a) Platoon scenario presented in [39] and b) platoon scenario presented in [40]. Grey arrows indicate the communication links carrying data among vehicles

vehicle adapts the inter-vehicular distance linearly based on its own speed and the time headway where reducing the time headway will increase the achievable benefits from platooning. However, it is noted that, for both constant and headway policies, maintaining the string stability is a major concern. For the constant policy, it was proven that the string stability cannot be guaranteed when platoon control systems make decision based only on the inter-vehicular gap [37, 38] while for the headway policy the string stability suffers when reducing the time headway [33, 35]. Through V2X communication, it is possible to mitigate the limitations of both constant and headway policies. For instance, a multitude of information obtained from all or a fraction of the vehicles in the platoon (e.g. acceleration of the lead vehicle, spacing error of other vehicles in the string, vehicles position, velocity and accelerations etc.) can guarantee the string stability of constant policy [37]. On the other hand, in the headway policy, CAVs can reach time headway up to 0.6 s [39]. Although achieving the time headways less than 0.6 s is possible for CAVs, experimental studies have shown that passengers confidence accepts time headways up to 0.6 s [28] while preserving string stability. Therefore, by increasing the range of information shared by vehicles in a platoon, better performance in terms of string stability can be achieved. For instance, in [39] it was shown that by including information from the vehicle ahead the lead vehicle (defined as second lead vehicle) into the control actions of subject vehicle¹ (see Figure 1a), it is possible to reduce the minimum time headways with respect to the case where only information from the lead vehicle was used without jeopardizing string stability. Another example is documented in [40] where it was proven that by including information from the following vehicle into the computation of the acceleration of the subject vehicle (see Figure 1b), it is possible to preserve the cooperative motion also when one of the vehicle in the string has limited speed performance compared to the other vehicles in the fleet. Thus, there is a proof from literature that varying the number of communication links has an effect on the string stability of a platoon. The idea of improving the performance and robustness of vehicle platoons by increasing the number of communication links between vehicles has recently motivated researchers to investigate the possibility of coordinating vehicle motion by using different communication network topologies² between vehicles of a platoon; see for instance [42, 43] and references therein. The focus of the platoon control system is then to guarantee platoon formation and stability independently from the underlying communication network topology while assuring robustness to uncertain and time varying communication delays.

However, the current literature does not provide a systematic approach either for the selection of the underlying network topology or for the information that vehicles in the platoon should share to achieve the synchronised motion, and usually only platoons with

¹Subject vehicle refers to the autonomous vehicle, performing a given task or maneuver, e.g. a lane change, crossing an intersection, cooperative driving in a platoon etc.

²A communication network topology is defined as the connectivity structure of the vehicular network [41], i.e. the pattern in which vehicles are connected in the platoon via wireless communications.

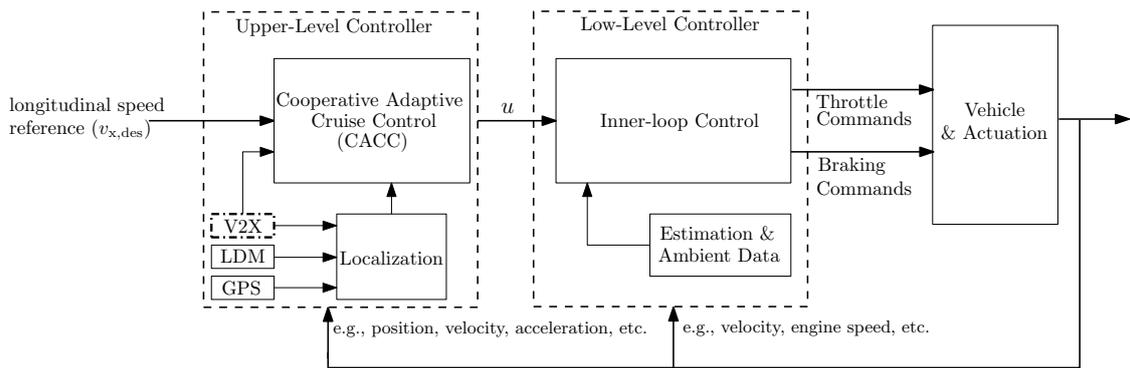


Figure 2. General control architecture for vehicle platooning.

homogenous vehicles (i.e. with equal acceleration/deceleration capability, equal actuator delays etc.) with the same preferences (such as spacing policy, time headway, etc.) are considered.

The information shared among the vehicles for maintaining the synchronised motion of the platoon depend on the vehicle dynamic model used for the design of platoon control algorithms. Usually, when the control objective is to impose individual and string stability, only the longitudinal vehicle dynamics is considered. According to the automotive literature, the longitudinal control system architecture for vehicle platooning is hierarchical where it is composed by an upper-level controller, known also as Cooperative Adaptive Cruise Control (CACC) system, and a low-level controller [44, 45]. The former determines either the desired acceleration or driving/braking torque for each vehicle based on information collected from its neighbours, while the latter is instead locally used to generate for each vehicle the throttle and/or brake commands required to exactly track the desired references as planned by the upper-level CACC. Figure 2 depicts the two-level platoon control architecture where the Estimation & Ambient Condition block is used to reconstruct information not directly measured (such as the air mass incoming into the engine) by on-board sensors and provide ambient data (such as road slope) to the Inner-loop low level controller, while the Localisation block is used to localise the vehicle on a Local Dynamic Map (LDM). The reference speed is provided to the leader by planning controllers, e.g., speed optimisation controllers for the minimisation of the fuel consumption of the fleet (see Section 5 for further details on speed optimisation supported by V2X communication), and the V2X devices are used to gather information from the neighbouring vehicle in the platoon.

It is noted that both the upper and the low-level controllers are designed based on the longitudinal vehicle dynamics. However, models with different fidelity have been used to capture the longitudinal motion, for instance, detailed models are adopted for designing inner-loop controllers while simple models are exploited to design CACC algorithms. Furthermore, it is noted that several simplified longitudinal vehicle models have been adopted in the technical literature for devising of CACC strategies. These models can be classified based on the order of the resulting dynamical system (i.e., the number of differential equations describing the vehicle state or motion) and they might contain nonlinear terms such as drag force and rolling resistance. Typically, simplified longitudinal vehicle dynamics are described using (i) first-order models (single integrators), (ii) second-order models (double integrators and linear/nonlinear damper-mass systems), and third-order models (linear/nonlinear third-order systems). When single integrators (first-order models) are used the vehicle state is the vehicle position and the vehicle velocity is used as control action [46]. On the other hand, second-order models describe the vehicle as a

point mass where the vehicle state variables are the longitudinal vehicle position and velocity while the longitudinal acceleration is used as control action [31, 47–49]. In case the drag force and rolling resistance are neglected, second-order models reduce to double-integrators [31]. On the contrary, if the drag force is relevant (e.g., in the case of platoons of trucks or cars driving at high speed), the longitudinal vehicle dynamics is described through a damper-mass system [47], which is linear when a linear approximation of the drag action is used [48]. In the case of third-order models the vehicle is still described as a point mass but an additional state is introduced to consider the time-lag in the longitudinal acceleration due to, for instance, the vehicle powertrain and engine dynamics, thus the control action is usually the reference driving/braking torque or the desired acceleration [32, 50].

First and second-order models have been considered in the literature to simplify the control design and the closed-loop analysis of platoon control system especially with respect of the platoon length, i.e., the number of vehicles in the platoon. For example, in [46] the single-integrator model was used to analytically show that the magnitude of the control action can scale with respect to the root of the platoon length. In [31] the double-integrator model was adopted to prove that the stability margin goes to zero as the inverse of the square of the platoon length when the bidirectional topology³ is used. In [48] it was shown that string stability can be preserved in presence of communication latency if the information shared through the V2X links are augmented with the leader velocity information. This result was achieved by using a second-order vehicle model which included also the drag force. However, to facilitate the closed-loop analysis a linear drag force was considered together with the perfect knowledge of the vehicle parameters. Consequently, unavoidable parameter mismatches and unmodelled nonlinearities can jeopardise string stability and safety in real working conditions. The need to design robust platoon algorithms with respect to vehicle nonlinearities and parameter uncertainties has been discussed for instance in [47] where a nonlinear damper-mass system with unknown parameters was used to model the longitudinal motion. In [47] authors suggested using a nonlinear controller with adaptive parameters to tackle vehicle uncertainties and disturbances while achieving string stability for bidirectional topologies. It is noted that when first and second-order models are exploited for the design of CACC strategies, it is implicitly assumed that the control action can be instantaneously imposed to the vehicle. On the other hand, this assumption might not be fulfilled due to inevitable parasitic delays and lags of the powertrain, sensors and actuators, which can jeopardise stability and performance of platoon control systems. In accordance to [35], a lumped parasitic delay and lag are the combined result of pure time delays and lags in (i) the engine response, (ii) the throttle actuator, (iii) the brake actuator, and (iv) low-pass filters used for sensors such as engine manifold pressure sensor, wheel speed sensor etc. In [35] authors also proved that when vehicles in the platoon receive only information from the predecessor vehicle, the time-headway has to be at least double of the sum of the lumped parasitic delay and lag to guarantee string stability, thus increasing inter-vehicular distance which results in less fuel efficiency and road usage [51]. For a constant spacing policy and vehicles modelled as a second-order point-mass system, authors have proven in [52] that string stability is preserved in presence of unknown but upper-bounded time-lags by reducing the magnitude of the control gains which might reduce platoon stability margins.

To systematically consider delays and time-lags, third-order vehicle models are used

³The topology is said to be bidirectional when each platoon vehicle gets information only from the predecessor vehicle and the follower vehicle (see also Figure 1b).

where an additional state is added to the aforementioned point-mass systems to capture either the dynamics of the acceleration of the vehicle or its torque. Usually, the additional equation is a low pass linear filter with unitary gain and time constant equal to a lumped value of the lags of the powertrain, sensors and actuators. The input to the filter is either the desired vehicle acceleration [32, 39, 53], desired driving/braking torque [50, 54], or a delayed version of these quantities to model also a lumped delay of the powertrain, sensors and actuators [35]. The analysis of the technical literature have shown that the lumped time-lag ranges from 200 ms to 800 ms, while the time-delay is with 20 ms and 250 ms [55]. Furthermore, both linear and nonlinear third-order vehicle models have been used for platoon control design. A nonlinear third-order model has been recently considered in [50] for the design of an optimal network based platoon strategy which also guarantees that the desired driving/braking torque is confined to a preassigned set. An additional example of the use of nonlinear third-order systems is provided in [54] where a nonlinear controller was designed to guarantee the convergence to zero of the inter-vehicular error in a finite time and it was shown that the converging time depends on the network topology. It is noted that, although nonlinear systems have been used, linear third-order models are more often adopted for CACC design as they simplify the stability analysis of the closed-loop system. For instance, in [39] it was proven that by including the desired acceleration of the second lead vehicle (see also Figure 1a) into the computation of the CACC action it is possible to ensure string stability also for time-headway smaller than the double of the sum of the vehicle time-lags and delays, thus improving the result in [35]. More recently, authors in [32] have proposed a systematic approach for design of the platoon control parameters based on the study of the roots of a third order algebraic equation whose coefficients depend on the vehicle time-lag, network structure and control gains, thus showing the coupling among control parameters, network topology and vehicle model to achieve the cooperative platoon motion. In [53] authors extended the previous analysis to prove that by enlarging information topology (i.e., adding communication links to the bidirectional topology) stability margin can be made dependent on the number of the vehicles in the platoon, thus improving the result in [31] for double-integrators vehicle model.

It is remarked that the longitudinal vehicle models discussed above are used to design CACC strategies to impose the synchronised motion to a fleet of consecutive vehicles. The output of these control algorithms is then imposed to the vehicle by low-level controllers [44, 45] (see also Figure 2). As the control variables of low-level controllers are the inputs to the vehicle actuators (e.g. throttle opening and the braking system), their design requires more detailed longitudinal vehicle models which also include the engine dynamics, engine maps, speed density functions, throttle body dynamics, dynamics of the braking system, nonlinear drag forces, rolling resistance and road slope etc. [44, 45]. The ability of the low-level controller to impose to the vehicle the commands provided by the upper-level controller is fundamental to achieve the cooperative motion, and controllers with poor tracking capability might induce larger transients and steady-state spacing errors, such as those numerically documented in [56], which might threaten road safety. It is noted that parameter uncertainties, unmodeled dynamics (e.g., engine/vehicle unmodeled dynamics), disturbances (e.g. wind) and changes in operating speed are unavoidable and prevent the perfect tracking of the commands generated by platoon controllers. Consequently, the dynamics of the vehicle with the low-level controller can differ from those predicted by using simplified longitudinal vehicle models. The mismatch between the simplified models and those provided by vehicle/low-level controllers motivates the use of uncertain systems subjected to bounded unknown disturbances for the CACC design. A systematic technique to model the low-level controller and the vehicle as a

third-order linear system with unknown but bounded parameters and disturbances for platoon applications has been recently proposed in [45]. Specifically, based on the range of the possible variations of the vehicle parameters, in [45] the authors used a detailed longitudinal vehicle with a nonlinear low-level controller to obtain a set of vehicle acceleration profiles. These acceleration profiles were then used to tune multiple third-order linear models with a multiplicative uncertainty to be exploited for the design of robust and adaptive platoon controllers, such as those presented in [57–59], which guarantee stability also in the presence of such model uncertainties. It is noted that, for the design of control algorithms to impose the cooperative platoon motion, usually, only the longitudinal vehicle dynamics is considered. However, for additional platoon operations, such as side merging into a platoon and leaving a platoon, also lateral vehicle dynamics must be modelled for the generation and tracking of lateral feasible trajectories [60, 61]. Lateral vehicle dynamic models are discussed in Section 3 for the planning and tracking of lateral manoeuvres for lane changes. These models are also those used for platoon functionalities that require lateral movements, thus the reader is referred to Section 3 for further details on lateral vehicle models for CAVs.

Finally, it is remarked that although V2X communication systems can help in ensuring string stability with reduced inter-vehicular gaps, the control of platoons in the presence of network imperfections (such as time varying and uncertain communication delays, and packet loss) is still a challenging open problem. Furthermore, even though several numerical studies have confirmed that organising vehicles in platoons increases fuel economy and road capacity; systematic platoon strategies for achieving a suitable compromise between safety and performance based on system parameters (e.g. inter-vehicular distance, platoon speed, network latency, and packet drop rate) are not available in the current literature.

3. Lane Change

Lane changes are common manoeuvres on highways and have a significant impact on transportation traffic flow and safety as they can induce speed and traffic flow oscillations especially in dense traffic situations [62]. Furthermore, vehicles performing lane changes act as moving obstructions which increase traffic shock waves and reduce safety [62]. Vehicles that can autonomously perform high speed manoeuvres have the potential to reduce the risk of lane change crashes, thus improving traffic safety [63]. However, to autonomously perform a lane change, it is essential that a vehicle can determine if, when, and how to perform a lane change. The decisions that govern “if” a lane change is required are dependent on factors such as (i) legislation, (ii) route plan, (iii) traffic conditions, etc. Once the decision to perform a lane change has been made, it is the need to identify the right instant i.e., “when” to initiate and terminate this manoeuvre to maintain both safety, comfort of the occupants and other road users. Finally, once the time and spatial boundaries are computed, the important task of actually performing i.e., “how” the lane change needs to be tackled by the CAV. Various approaches proposed in literature for performing these tasks are discussed in further detail below.

According to [64], two types of lane change are possible: (a) discretionary lane change (DLC) and (b) mandatory lane change (MLC). MLCs are either imposed by the traffic rules or by vehicles destinations to follow their desired route, e.g. for the correct selection of the lane for merging onto the highway from an on-ramp or taking an exit off-ramp. Contrary, for DLCs the change of lane is performed if the traffic situation is perceived as better in the destination lane (also denoted as the target lane); for example, allowing the

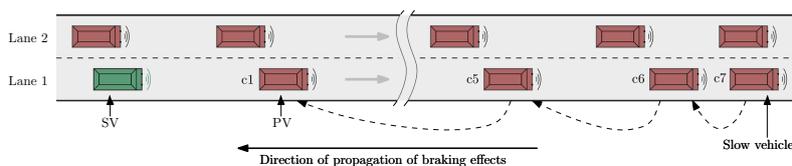


Figure 3. The traffic scenario, where a leading vehicle ($c7$) in the preceding traffic runs slowly that affects the traffic flows on lane 1. The lane change and speeding behaviour of the subject vehicle (SV) (based on the scheme in [68]).

subject vehicle to maintain or increase speed or to pass a sequence of moving vehicles with a possible return to the origin lane (overtaking). A fundamental step in any DLC is the Lane Selection [64], which is defined as the process of choosing the target lane through foreseeing an improvement in the driving condition. Autonomous vehicles can select the target lane based only on the data collected from nearest vehicles, i.e., those within the line of sight of on-board sensors [65, 66]. Nevertheless, limited knowledge of the traffic ahead is a key issue to lane selection as it might generate incoherent lane change decision making (e.g., non-beneficial lane change). By assuming a V2X environment, where traffic information for both the current lane and adjacent lanes are known in advance, each connected vehicle can select a sequence of lane changes over a given horizon with the aim to optimise an individual cost function (travel time, driver comfort etc.) This approach for lane selection has been used in [67, 68] where an optimal strategy has been exploited to compute both the optimal lane and acceleration of the subject vehicle, over a finite horizon to minimise a cost function related to the driving efficiency and comfort. The effectiveness of including traffic information of an entire road segment for the optimal selection of the target lane has been proven numerically in [68] in which two simulation case-studies were considered. In the first scenario, shown in Figure 3, there is only one subject vehicle indicated as SV. The SV is initially in lane 1 and is preceded by the vehicles $c1, c2, \dots, c7$. Only vehicle $c1$, also indicated as PV (Preceding Vehicle) in Figure 3, is in view of the subject vehicle (see also Figure 3). The 7th preceding vehicle ($c7$), which is beyond the sight of the SV, suddenly decelerates between $t = 2$ s to $t = 5$ s and its velocity drops from 60 km/h to 35 km/h and then continues moving slowly. This slow vehicle gradually affects the traffic downstream, e.g. from the 6th vehicle ($c6$) towards the 1st vehicle $c1$. The scenario described in Figure 3 is then analysed considering the following cases, (i) on road vehicles are not connected and the subject vehicle senses only the position of vehicle $c1$ and lane selection is performed by using a set of rules; (ii) a connected environment is assumed and the subject vehicle can sense in advance the velocity reduction of vehicle $c7$ via communication networks and use this information to change its longitudinal and lateral motions before vehicle $c1$ starts to slow down.

Numerical results show that in the case where the subject vehicle does not have a view of traffic conditions on the road segment beyond its sight (case (i)), it must reduce its velocity from about 58 km/h to 35 km/h (a velocity reduction of about 40%) before initiating a lane change manoeuvre at $t = 30$ s. But, when traffic information is included (case (ii)), the lane change manoeuvre initiates at $t = 16$ s and the velocity for the subject vehicle is reduced at most by 17.25%. Intuitively, the latter vehicle response improves both the average vehicle speed and fuel economy as well. When the optimal lane change is used, the average velocity increases about 7.72% while fuel consumption is reduced about 40%. For accurately evaluating fuel reduction in more realistic conditions, a mixed scenario was also simulated where a road segment of 2 km was considered with three lanes including a merging lane. Energy consumption on the road segment was evaluated for different penetration rates. In addition, results were compared with respect to the cases:

(a) no vehicle is equipped with the optimal selection of the target lane and (b) some vehicles adopt Cooperative Adaptive Cruise Control (CACC). Numerical results showed that the optimal lane selection based on traffic information always provides better performance in terms of fuel economy with respect to the CACC by improving full economy up to 14%. Also, with low penetration rate the optimal lane selection provides consistent improvement of fuel economy compared with no vehicle so equipped. For instance, with a penetration rate of 10%, a fuel economy of about 8.8% is obtained. Controlled vehicles in a mixed scenario also improve fuel economy of conventional vehicles. For instance, when the penetration rate is 25%, the fuel reduction of all vehicles is 9.2%. Such additional benefit is due to the intrinsic cooperation among vehicles that share the same road section. Indeed, some of the conventional vehicles must adapt their velocity and target lane with respect to the controlled ones to avoid collisions.

For the lane selection method described above, each vehicle selects a sequence of target lanes using off-board data collected via V2X communication by optimising a cost function that weights only individual performance indices (fuel consumption, travel time, etc.). Hence, this approach does not exploit the potential of V2X communication to create cooperative driving scenarios aiming to improve the traffic flow, pollutant emissions and fuel consumption of road networks. To improve the use of road infrastructures, in [69–71] cooperative lane selection methods have been proposed. The common idea underlying these methods is to measure the performance of a group of vehicles and select the set of lanes that guarantees the minimisation of a common cost function. When these methods are adopted, the road is divided in segments and at the beginning of each segment the following steps are performed:

- *Data collection*: A group of vehicles is formed and information from each vehicle is collected through communication links. These data can include location, speed, lane and desired driving speed of each individual vehicle.
- *Optimal target lane determination*: Based on the data collected in the previous step the target lane for each vehicle in the group is computed by minimising a collective cost function (e.g. a cost function that includes the energy consumption or the travel time of the group).
- *Lane change execution*: Each vehicle in the group executes the required lane change within the current road segment.

For cooperative lane selection, both Centralised and Distributed solutions have been proposed. Centralised algorithms use one control unit for selecting the target lanes for the vehicles in the group and data are collected via V2I communication links, while in the case of Distributed solutions, the set of the vehicles in the group cooperate to select the target lanes to minimise the common cost function by using V2V communication links. In the following, some examples from the literature are reported. In [69, 70] a distributed optimal lane selection for minimising the travel time of a vehicle which travels on a highway has been proposed. The effectiveness of reducing the travel time has been shown numerically in simulations for four-lane highway with three entries and three exit points. Numerical results indicated that the average travel time reduction of the proposed solution depends on traffic density and the percentage of cooperative vehicles. For instance, it was shown that if the traffic density is 2000 vehicle/hour with a penetration rate of 100% the average travel time reduction would be 14.3% compared with the case that no vehicle is connected, while it would be 6.25% if the penetration rate is 50%. On the other hand, with considering a traffic density of 6000 vehicle/hour with 100% penetration, the maximum fuel reduction would be 8.8% compared with the case where no vehicle is connected. In [71] a centralised cooperative lane selection has been proposed to minimise the

travel time of the group. The method was tested numerically for a highway segment 2000 meters long. Furthermore, different volume-to-capacity (V/C) ratios, ranging from 0.5 to 0.95, were considered. Notice that the V/C ratio is a measurement of the traffic status based on the current traffic volume and capacity of the road segment, which is defined as the maximum number of vehicles per unit time which can be accommodated on the road segment under given conditions, e.g. a given time headway between consecutive vehicles [72]. Simulation results confirmed a travel time reduction of up to 3.79% when the V/C ratio is 0.7. The reduced traveling time has an effect also on the fuel consumption and pollutant emission with reductions about 2.2% and 19%, respectively.

Analysis of the literature has shown that lane changes resulting from limited information and lack of cooperation among of road vehicles have an impact of the traffic flow, travel time and fuel consumption. Through the use of CAVs, it is possible to; (i) improve the lane selection process of individual vehicles by using off-board traffic data and (ii) enable cooperative scenario where a group of vehicles collaboratively choose their target lane. However, lane selection solutions which use V2X communication only for gathering additional off-board information do not completely exploit the potential of communication channels to create cooperative driving scenarios where sets of vehicles decide together future actions to improve the overall traffic. The results presented in this section have shown that cooperative lane selection is possible and it is beneficial for fleets of vehicle to increase fuel efficiency and to reduce travel time thereby increasing road throughput. On the other hand, the concept of deciding a set of target lanes by optimising a single cost function for a group of vehicles implies that some of the vehicles in the group might worsen their performance (e.g. fuel consumption, traveling time etc) with respect to the case of no cooperation. Consequently, this approach might be used by road authorities to improve traffic but it might not be suitable for controlling individual vehicles which might aim to get individual benefit (unless individual benefits can be demonstrated as well). Finally, even though individually based and cooperative lane selections supported by V2X communication have shown to provide similar benefits, it is not possible to compare them quantitatively. The results presented depend on a range of factors such as the simulator, traffic scenario, control strategy etc. which makes a systematic comparison impossible.

Once the decision (either MLC or DLC) to perform a lane-change has been made, the autonomous vehicle needs to (i) generate a feasible collision-free trajectory in real time, and (ii) track this trajectory as closely as possible by applying appropriate amount steering, acceleration and braking action. Performing an autonomous lane change manoeuvre is a challenging task as it combines both lateral and longitudinal motion of a subject vehicle while avoiding collisions with other road users [73]. The two control tasks mentioned above for achieving this goal are divided into (i) trajectory planning, and (ii) trajectory tracking. A general control architecture to depict the closed-loop structure is shown in Figure 4 [74–79]. The trajectory planning controller perceives the environment, monitors vehicle states (longitudinal and lateral positions, longitudinal and lateral velocities, longitudinal and lateral accelerations, and heading) and computes safe and feasible trajectories (e.g., reference velocity, v_{ref} , longitudinal and lateral position, denoted in Figure 4 as X_{ref} and Y_{ref} , respectively) for the vehicle to track [80]. The trajectory tracking controller then computes, via feedback algorithms based on the tracking error, the necessary torque (τ_{ref}) and steering inputs (δ_{ref}) required to track the reference, despite possible measurement noise, un-modelled dynamics, parametric uncertainties which may or may not be accounted for by the trajectory planning controller.

An autonomous vehicle performing lane changes at high speeds requires that vehicle dynamics and constraints are considered while planning trajectories so that in addition

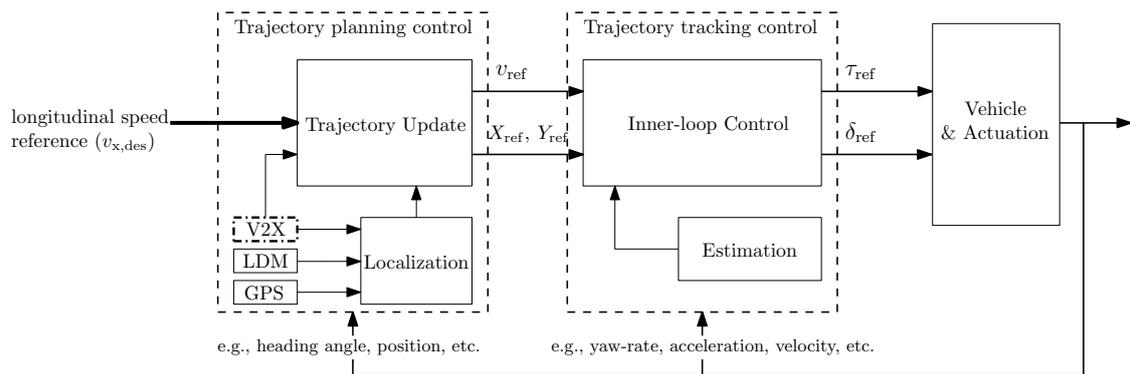


Figure 4. General control architecture for an autonomous vehicle (V2X block with dot-dash boundary: optional functionality)

to being safe are also feasible. Thus for autonomous high-speed driving, the vehicle model provides two pivotal functions, (i) vehicle system simulation, and (ii) design and investigation of controller properties [81]. A variety of vehicle models ranging from point-mass model all the way to multi-body models have been developed and the ones relevant for controller design have been documented in [30]. Since, the lateral dynamics of a vehicle has a nonlinear dependence on the longitudinal velocity, vehicle models that provide a suitable trade-off between model accuracy and fidelity need to be used for trajectory planning. A comprehensive review of different trajectory planning techniques in [82] shows that there are three vehicle models namely (i) the point-mass model, (ii) the linear kinematic bicycle model, and (iii) the non-linear kinematic bicycle model which are most commonly used by researchers. Among these, the point-mass vehicle model does not incorporate any lateral and yaw dynamics of the vehicle and hence trajectories involving lateral motion that were generated using this model were often found to be unfeasible under certain conditions (especially at high speeds and/or low friction coefficient). The two bicycle models mentioned above capture the lateral and yaw dynamics by modelling them using geometrical relationships. This additional system dynamics means that kinematic bicycle models are suitable for trajectory planning even in conditions of high speed and low friction coefficient [78].

As explained above, the planned trajectory is provided as the reference to the tracking controller to be accurately tracked while maintaining also state and input constraints. A comprehensive review of trajectory tracking control on the aspects of choice of vehicle model, control strategies, and controller performance criteria has been performed in [81]. The review demonstrated that geometric models based on Ackermann steering are not suitable for high-speed trajectory tracking due to their inability to include vehicle dynamics (e.g., acceleration and velocity). Additionally, it is highlighted that kinematic models (bicycle or four-wheel) are also unsuitable for high-speed trajectory tracking as they are inaccurate due to assumptions such as (i) no side-slip in tyres and/or vehicle, and (ii) linear tyre behaviour throughout the entire range of operation. Dynamic vehicle models (full vehicle model, half vehicle model, and bicycle model) attempt to address these issues by incorporating additional states such as (i) vehicle side-slip angle (β), (ii) tyre side-slip (α), and (iii) linear or non-linear tyre models and they were found to provide a more accurate representation of a vehicle during high-speed driving [81]. Moreover, for manoeuvres (lane-change manoeuvre, overtaking manoeuvre, highway driving) that require small lateral accelerations ($\leq 0.5g$) and low vehicle side-slip angles ($\leq 5^\circ$) the tyres remain within the linear region of operation and hence, a dynamic bicycle model (linear) is sufficient to capture the relevant dynamics of a vehicle [81, 83]. As a

result, a majority of papers in literature have used a single-track vehicle model (bicycle model) for developing a tracking controller for performing lane change manoeuvres since this manoeuvre is performed well within the dynamic limits of the vehicle (i.e., lateral acceleration, vehicle side-slip, and yaw-rate) where both the vehicle as well as tyre dynamics can be approximated by linear models. However, while performing lane changes at high-speeds and/or in low road friction conditions, the tyres might operate in the non-linear region which might lead to the lateral and yaw dynamics of the system to exhibit substantial non-linear behaviour and therefore for appropriate scenarios either nonlinear models, linear parameter varying (LPV) models or multiple models can be used to capture the relevant dynamic behaviour of the system [83, 84]. Out of the wide variety of vehicle models available in literature a kinematic bicycle model and dynamic bicycle model have been found to provide a good compromise between model complexity and accuracy for controller design related to highway driving applications [85, 86]. For a more detailed discussion on different vehicle models the reader is directed towards the work by [81, 87–89].

4. Intersection Management

Intersections are shared areas (or conflict areas) and represent bottlenecks in the traffic flow. They can be classified as (i) Signalised Intersections which are equipped with traffic lights, and (ii) Non-Signalised Intersections which do not have traffic lights and drivers must interact with each other. Although intersections represent a small fraction of the road system, a noteworthy amount of fatalities occur within the area jointly used by the intersecting streets and are mainly caused by human errors [90]. For example, during the 10-year time period from 2005-2014, over 20% of the fatalities on EU roads took place at intersections [91]. Furthermore, ineffective intersection management (e.g. traffic lights with fixed timing, stop signs etc.) can increase the time that vehicles are stationary at junctions thereby resulting in an increase of travel time, fuel consumption and pollutant emissions. Hence, the correct management of intersections is of utmost importance for keeping traffic safe, improving traffic flow, and at the same time reducing energy consumption, pollutant emissions, and travel time. Autonomous vehicles and their cooperation with intelligent road intersections can reduce human mistakes and improve the efficiency of intersection management systems, thereby improving safety, energy, and traffic efficiency [92]. In addition to traffic timing, V2X communication systems can be used to provide detailed vehicle information and driver's intentions of vehicles approaching the intersection. Such information can be collected and exploited to anticipate the behaviour of the vehicles, particularly those that are not within the line of sight of the on-board systems of the subject vehicle. Therefore, this section is devoted to analysing the working principle of Cooperative Intersection Management (CIM) systems. Hereafter, a CIM system refers to those intersection control systems which exploit V2X communications to provide solutions to the problem of coordinating the motion of a set of vehicles through intersections safely and efficiently. The management algorithms for CIM solutions are mainly based on heuristic rule-based methods [92] or optimisation based methods [93]. In the case of heuristic rule-based methods, the vehicles cooperate to pass the intersection by using a set of fixed rules implemented as an interaction protocol among the vehicles and the coordination unit. On the other hand, optimisation-based methods mathematically formulate a CIM problem and solve it by using tools from control theory. It is noted that the decision variables (also known as control variables) depend on the adopted method. They can be the timing of traffic lights, time slots to each vehicle to

pass the intersection, intersection passing sequence, acceleration and deceleration, etc. In what follows, CIM solutions for signalised intersection and non-signalised intersection are analysed to identify potential benefits and limitations of each method for autonomous driving systems.

In signalised intersections, the safety requirement is usually assumed satisfied under the implicit hypothesis that all the vehicles respect the traffic light signals. Therefore, the objective of CIM systems can be to reduce idling at red lights to maximise traffic flow or to improve fuel efficiency. The idea behind these controlling systems is to use information collected by means of V2X communication links to adjust vehicles motion with the aim to reduce idling and fuel consumption at red lights. Typically, it is assumed that vehicles approaching the intersection can communicate with the infrastructure and receive information from the upcoming traffic light. This information can be either the current state of the traffic light or the Signal Phase and Timing (SPaT) signal, i.e. the current state and timing of the upcoming traffic light. Based on this information, the velocity profile of each vehicle is accordingly modified to pass the intersection during green light windows. Example of rule based methods for computing the vehicles speed profile can be found in [94] and [95]. Usually, rule based methods compute the vehicle speed profile based on the current state of the upcoming traffic light and do not consider vehicle dynamics within the design criteria. Conversely, when optimisation methods are used, the speed profiles are the solutions of dynamic constrained optimisation problems where the objective is to reduce the fuel consumption over the whole trip [96] and [97] or to minimise the travel time [98] and [99]. In this case, common constraints of an optimisation problem are longitudinal vehicle dynamics, maximum allowed vehicle speed, inter-vehicular distance, and acceleration/deceleration capability of a vehicle. Furthermore, the accuracy of the optimisation algorithms can be enhanced if the precise position of traffic lights along the path, the SPaT information of traffic lights, and upcoming road parameters (e.g. road surface friction, maximum speed velocity) are known. Therefore, V2X communication systems have the potential to enhance the accuracy and efficiency of current optimisation algorithms by providing to a subject vehicle upcoming environmental and SPaT information. However, the SPaT information cannot be accurately obtained from traffic lights that adapt their timing based on the vehicle queue in each road segment approaching the intersection [100] and [101].

The current literature conforms that if all on-road vehicles can adjust their speed based on SPaT information, considerable fuel reduction can be achieved compared to the case where no vehicle is connected. For instance, in [97] it was shown that when all vehicles are connected and follow precisely the speed profile based on the SPaT data, in the case that the traffic density is 600 vehicles/hour/lane, the average fuel reduction would be 30% compared with the case where all vehicles are unconnected. Also, it was shown that in the case of mixed traffic scenario (i.e. a mixture of connected and human driven vehicles), the achievable increase of fuel efficiency depends on the fraction of connected vehicles (i.e. penetration rate). Moreover, by increasing the fraction of connected vehicles in a traffic segment, unconnected vehicles are more likely to adapt their motion to match the speed of surrounding connected vehicles where higher synchronisation of vehicle motions results in reduced stoppages at the intersection, thus bringing down overall fuel consumption for connected as well as unconnected vehicles. However, assessing the real benefits of CIMs for signalised intersections in a mixed scenario is not trivial as results are sensitive to the simulated scenario (e.g. number of lanes, traffic flow, etc.), adopted method for computing the speed profile, and the numerical tool used to simulate the human driven vehicles (e.g., Car-following model; Lane-changing model). Therefore, discordant results on fuel reduction as a function of the fraction of the equipped vehicles

are reported in the literature. For instance, in [95] the trend of the fuel consumption for connected, unconnected, and all on-road vehicles were decreasing as a function of the penetration rate. Furthermore, fuel consumption of connected vehicles was larger than that of unconnected vehicles for a penetration rate less than 60%. In [102], it was noted that if the penetration rate of connected autonomous vehicles was less than 25%, an increase in fuel consumption for all road users, up to 5%, was measured. However, the fuel efficiency of the all road users became a positive increasing function for penetration rates higher than 30%. In [97], it was observed that the average fuel consumption of connected vehicles was always much smaller than those unconnected. However, for high density traffic of 900 vehicles/hour/lane, the fuel consumption of connected vehicles increased with the penetration rate. This unwanted effect was caused by the impossibility of connected vehicles to implement their optimal speed profiles in high traffic density. It is noted that in the abovementioned research papers, only the traffic light information was considered to optimise the speed of connected autonomous vehicles. However, V2V communication systems can be also used to gather additional information such as neighbouring vehicle states to further improve fuel efficiency. For instance, in [103] and [104], an optimisation control algorithm which utilises both V2I (SPaT) and V2V communication was proposed. The idea behind the approach was to adjust the motion of each connected autonomous vehicle with respect to the velocity of its successor to possibly allow both vehicles to cross the intersection in the same green light window. In the scenario of having a string of 15 vehicles on a road and traffic lights located every 500 m, the simulation results showed that the fuel economy of traffic utilising both V2I and V2V information can be improved by 22% compared to the case when just V2I information is available and 50% compared to the case that the cooperation is not used. In [102], V2X communication systems were also used to broadcast the length of the queue stopped at the upcoming traffic light, thus to adjust the vehicle motion to avoid stoppages behind traffic. Numerical results showed that by including traffic data in the computation of the speed profile, it is possible to further increase fuel efficiency with respect to the case where only SPaT information was used in mixed traffic. However, this increase was limited to 2%.

In non-signalised intersection, as there are no signals or sign-posts available, vehicles must coordinate the use of the common area within the junction. This coordination problem is usually formulated as calculating the trajectories for individual vehicles that allow them to safely reach their destination in a finite time. According to [105], any solution should meet the basic requirements of safety and liveness (defined below), while optimising performance metrics (e.g. fuel consumption, travel time, etc.). Here, safety means that there is no collision between pairs of vehicle crossing the intersection whereas liveness guarantees that all vehicles enter and exit the coordination area in finite time so that permanent stops and traffic deadlocks within the intersection are avoided. It is noted that despite the management of signalised intersections in which vehicles can be either just connected or connected autonomous, for the management of a non-signalised intersection, a common assumption is that all vehicles are connected and autonomous. For the management of a non-signalised intersection, Ref. [106] proposed a rule-based approach known as resource-reservation scheme. Achievable mobility and environmental benefits were reported in [107] through testing the method for a four-way intersection. The average delay to pass the intersection, fuel consumption, and pollutant emissions were compared with traffic lights and roundabouts. The simulation results in [107] indicated that the resource-reservation method always outperform current traffic lights and roundabouts regardless of traffic density. The average reduction in travel delay and fuel consumption with respect to traffic lights and roundabouts were 50% and 20%, respectively. Also, pollutant emissions such as HC, NO_x, CO were reduced by replacing traffic

lights with CIMs. On average, the HC reduction was 35%, while NO_x and CO reductions were 33% and 43%, respectively. The application of resource-reservation method was the subject of other research as well, e.g. [108] and [109]. However, their findings and results are in agreement with the outcome of [107]. Although a rule-based method can be more effective with respect to the roundabouts and traffic lights, its performance and the safety and liveness requirements are not guaranteed for events which have not been considered in rule definitions. As a result, the general lack of formal guarantees in terms of the object and constraints form the main weakness of rule-based solutions [105]. On the other hand, the main idea behind optimisation-based methods is to reformulate the problem of coordinating a set of vehicles through an intersection as an optimisation control problem [105]. The requirements of safety and liveness are recast as constraints of the problem while minimising the performance metrics. Collision free and deadlock free solutions are achieved by imposing constraints on the motion trajectories of vehicles. In this approach, for each pair of vehicles, it is required that the travel trajectories do not cross each other (safety requirement). In addition, each travel trajectory must enter and leave the common area of the intersection in a finite time (liveness requirement). Examples of optimisation based strategies can be found in [110–113]. In [110] and [111], the objectives of the minimisation was the travel time and it was numerically proven that optimal based CIMs can outperform intersections controlled thought traffic lights, roundabouts and all-way stop control in terms of fuel efficiency and travel time and for different road condition (dry, rainy and snowy). In [112] the target was to minimise the overlap of the vehicles position inside the intersection zone. Namely, the acceleration profiles of the vehicles were computed such that only a limited number of vehicles are present inside the intersection at each time instant. Numerical results showed that optimal based CIMs have the potential to reduce fuel consumption with respect to intelligent traffic light, i.e. those where the timing depends on the traffic queues behind the stop bar, especially for the case when traffic volumes exceed the capacities of the roads. In [113], a multi-objective optimisation approach was used in which the cost function included a term to penalise speed variation with respect to a speed reference, and a term to penalise excessive acceleration/deceleration. It was numerically proven that the optimal CIM was able to double the traffic flow compared to the case where traffic lights were used for coordinating a four-way intersection. Although optimisation based approaches consider vehicle dynamics and physical constraints to assure collision-free and deadlock-free solutions, the time to reach the optimal solution exponentially increases with the number of conflict relationships among the vehicles [105, 114]. For these reasons, the optimisation-based approach becomes numerically intractable for real-time scenarios. To address the computation issues associated with optimisation-based methods, in [114] authors have proposed a sub-optimal solution in which a controller calculates the occupancy time interval (i.e., the optimal time instants that must be used by each vehicle to safely enter and leave the intersection) based on shared information of traffic vehicles. Then, based on the allocated time instances, each vehicle computes its own optimal trajectory so that a local objective is minimised. The effectiveness of the method to solve the intersection problem was demonstrated through simulations. Furthermore, a set of 1000 simulations was analysed to assess the average time to solve the optimisation problem with and without the proposed solution. Analysis of the simulation results showed that the average time to solve the optimal control problem was about 10.14 s with a standard deviation of 24 s. On the other hand, when the proposed method was applied, the average computational time reduced to 0.043 s with a standard deviation of 0.022 s. Regarding sub-optimality of the solution, numerical results showed that the approximated algorithm gave results 20% less accurate than an optimal solution for about 85% of the random realisations.

The aforementioned survey for intersection management showed that integration of V2X communication systems improved the performance of autonomous vehicles; however, the level of achievable benefits depends on the case study, simulation scenario, type of intersection, etc., in both signalised and non-signalised intersections. Also, it depends on the quality of communication signals in terms of packets loss, packet errors and latency.

Contrary to the use-cases discussed in previous sections, the main focus of intersection management is more towards accurate modelling of intersection area and traffic flow rather than modelling the detailed motion of each vehicle at the intersection. Furthermore, the primary concern for non-signalised intersections is to guarantee a collision free path for each vehicle while for signalised intersections, it is to reduce energy consumption. As a result, vehicle models at different levels of abstraction are utilised for each problem and are discussed in further detail below.

For non-signalised intersections, where collision avoidance is the primary objective, it is imperative to ascertain a vehicle's position on the road with respect to time. Furthermore, as the subject vehicle can either maintain its lane or turn at the intersection, it is important to employ vehicle models that capture both longitudinal and lateral motion of the vehicle. For studies based on non-signalised intersections where the vehicles cross the intersection without turning, point-mass vehicle models, which are similar to third-order models discussed in Section 2, are most commonly used for this purpose as they provide a reasonable approximation of the planar motion (no vertical motion) [92, 107, 111, 113]. The position, velocity, and acceleration of the subject vehicle are the vehicle states used to control the vehicle on given portions of the road segment [105, 112]. The road-load equation of a vehicle to generate a state-space model of the vehicle is another technique proposed for capturing the longitudinal dynamics of a vehicle. The application of this vehicle model is demonstrated in [111]. Moreover, some studies also consider the possibility that the vehicles can turn at the intersection and the researchers propose the use of kinematic bicycle model as discussed in Section 3 to capture the non-holonomic motion of a vehicle with sufficient accuracy [109].

Signalised intersections pose a different challenge for vehicle modelling because of the twin requirements of (i) optimising a vehicle's velocity and acceleration to reduce time spent waiting at the signal, and (ii) reducing the amount of energy consumed in successfully navigating through a signalised intersection. Thus, vehicle models with simple dynamics to capture longitudinal motion and its effect on fuel consumption are commonly employed by researchers. The longitudinal motion of the vehicle is often modelled using the road load equation with velocity and acceleration being the two states of the system, i.e., the second-order model discussed in Section 2 [98, 99, 103, 104]. Moreover, an optional third state of the system is the energy consumption that is modelled as a function of the first two states which is then used within the optimisation routines discussed above within this section to optimise the velocity of the vehicle while minimising fuel consumption as part of a multi-objective optimisation problem [96, 97].

5. Vehicle Energy Management

CAVs have the potential to increase fuel economy by operating vehicles engines in regions with high efficiency which can result in a reduction of fuel consumption [115]. Communication channels can be exploited to provide partial or complete trip information augmented with real time information (traffic condition and weather, etc.) to the on-board control systems. These predictions, also known as preview information, can be then used for optimising the vehicle speed or vehicle powertrain to minimise fuel

consumption over the entire trip [116]. Systems optimising the global vehicle speed trajectory are known in the literature as Speed Advisory Systems (SAS). Global optimal speed advisory systems provide the optimal speed profile over the entire trip, ideally for the entire source-destination route. However, global optimal solutions are not easily tractable since the computational burden increases exponentially with the number of states and control variables. This drawback is known in optimisation literature as the curse of dimensionality [117, 118]. In addition, as the traffic on a road is highly dynamic and unpredictable, each vehicle needs to periodically update its optimal velocity profile based on the current traffic condition. For these reasons, the use of off-board computing for transportation systems has been proposed to assist vehicles with computation of the optimal speed profile [119, 120]. When this approach for speed optimisation is adopted, each vehicle uploads its information, e.g. destination, current velocity and position, to an off-board computing system which computes the optimal velocity profile and sends it back to the vehicle. For example, in [119] a cloud-based system was used as an off-board computing system. The system was tested experimentally both for urban and highway scenarios. For both scenarios three runs were considered : (i) the driver drove using his normal driving style and the speed advisory system was turned-off (these runs are referred to as baseline driving); (ii) the vehicle was connected to the cloud and received the optimal speed profile but the driver was responsible for controlling the vehicle to impose the optimal speed (these runs are referred to as advisor following); and (iii) the vehicle was assumed to be connected and autonomous and the optimal speed profile was imposed through an ACC system (in this paper these runs are referred to as intelligent adaptive cruise control). The fuel consumption reduction was computed by considering the fuel consumption obtained via the advisor following with respect to the baseline driving, and the fuel consumption of the intelligent adaptive cruise control with respect to the advisor following case. With respect to the baseline, the SAS improved fuel efficiency for the highway driving from 10.6% to 14.4% (with an average gain of 12.6%), while in the case of urban driving scenario, the fuel improvement was in the range of 8.1-20.9% with an average improvement of 12.5%. The analysis provided in [119] also shows that by combining SAS with ACC, additional fuel reduction can be achieved. By removing the human variability in following the advice speed, on average an additional 2% fuel reduction is obtained for highway driving while an improvement of 6.3% can be achieved for urban driving. The SAS proposed in [119] has been recently enhanced by IBM and Clemson University by including traffic light information [120]. Furthermore, to tackle the computational complexity, a parallel computing system was used as an off-board system to compute the global optimal speed profile. The optimisation algorithm implemented by exploiting the parallel computing framework was denoted as FastVO (Fast Velocity Optimisation). The effectiveness of the enhanced FastVO was also experimentally tested by the authors. The fuel consumption of FastVO was compared with a global optimal solution proposed in [119] and a Predictive Cruise Control (PCC) presented in [121]. It is important to point out that the global optimal solution was also implemented in the off-board system but without taking advantage of parallel computing and it does not consider the state of the traffic lights (in accordance to [119]). In addition, when PCC is used, the vehicle receives the optimal speed profile as a function of the traffic light ahead. This solution might be different from the global optimal solution as the optimal velocity profile was computed only when the vehicle is sufficiently close to the traffic lights. In terms of fuel consumption, the outcome of the experimental analysis showed that FastVO is always better than that of the global optimal solution and the PCC strategy. In addition, the final fuel reduction of FastVO with respect to the global optimal solution was about 32% while it was about 11% with respect to the PCC strategy. These experimen-

tal results can be explained as follows. As the solution in [119] does not consider traffic lights, vehicles can stop at intersections, thereby reducing fuel economy. Consequently, the additional idling phases increases the fuel consumption compared with the solution in [120]. When the PCC is used, the subject vehicle lacks the global information, and it can only determine its own velocity profile according to the traffic light ahead and hence cannot achieve a globally optimal solution. FastVO considers traffic lights and achieves global optimal velocity profiles, thus producing the least fuel consumption. The speed advisory system based on the use of off-board computing has been recently extended to a platoon of vehicles to further increase fuel reduction [122–124]. In [122] the optimal platoon speed was selected as a trade-off among minimisation of the travel time, fuel consumption and pollutant emissions. In addition to the speed, the authors adapted also the time headway along a planned route in hilly terrain. Numerical results showed that for a homogenous platoon (all vehicle being equal) tight platoon formation is the optimal choice, but when controlling a fleet of heterogeneous vehicles, the optimal spacing depends on the road slope and the position of the vehicle in the string. Furthermore, it was shown that, by optimising the platoon speed, the overall fuel consumption was reduced by about 10% with respect to the case of vehicles driving alone with no platooning. In [124] the authors assumed that information about the traffic state ahead can be broadcasted through V2X communications systems. Platoons can then be informed in advance of the presence of congestion along the road where the velocity must be reduced in accordance to the traffic level. By including velocity information of the traffic ahead in the computation of the optimal profile, it was shown by numerical simulation that a fuel reduction up to 80% could be possible.

It is expected that future autonomous vehicles will be either fully electric or hybrid-electric which makes analysis of cooperative energy management developed for current electric and hybrid electric vehicle important [125]. It is noted that in the case of Hybrid Electric Vehicles (HEVs), efficiency highly depends on the strategy for determining the split of power request between the combustion engine and the electric machine [126]. According to the technical literature [127], energy consumption of electric and hybrid/electric vehicles depends on the state of charge (SoC) of the battery. Using this variable, it is possible to optimise the power split ratio between power sources. When preview knowledge of driving profile is known in advance, the SoC profile can be scheduled in advanced through an off-line optimisation. However, these methods perform poorly when the driving route conditions change due to variations in traffic conditions. This drawback can be overcome by connectivity as it provides access to real-time traffic data which can be used to improve the prediction of future driving cycles. The opportunity to use real-time traffic data gathered via V2X communications to reduce energy consumption has recently been investigated for example in [128]. In this study, the average velocity of traffic was provided to the subject vehicle as preview of the traffic situation ahead. Based on these data, the subject vehicle computed the optimal SoC profile and, then, the SoC profile was used to optimise the power split with the aim of minimising energy consumption. In this study, the preview information was provided to the optimisation algorithm as 1) static traffic information where the vehicle obtained the traffic velocity information only once at the beginning of the trip (i.e. the first generated SoC reference trajectory was assumed to be relevant until the end of the trip) and 2) dynamic traffic information where vehicle obtained the traffic velocity information periodically (every 300s). The energy consumption provided by the strategy was evaluated by considering a real-world highway driving scenario based on collected traffic flow data from the Mobile Century project [129]. To better point out the benefit in terms of achievable energy reduction, the proposed controller was compared with a heuristic-based control algorithm

(i.e. when no traffic information is available). Simulation results showed that the static solution (i.e. algorithms with static information) reduced the fuel consumption by 1.84% compared with a heuristic-based method. The fuel reduction was 5% with the dynamic strategy (i.e. algorithms with dynamic information). Numerical results confirmed that better fuel reduction can be achieved by including traffic information during computation of the SoC profile. Furthermore, the highly dynamic nature of the traffic must be considered to further increase fuel economy. When traffic information is used to re-compute the optimal state of charge trajectory, the fuel economy can more than double with respect to the static solution. It is remarked that, the use of traffic data to improve fuel efficiency of connected hybrid vehicles has been documented also in some recent review papers on the energy management of hybrid powertrains such as [130–132] and can be directly applied to CAVs with hybrid or electric powertrains.

Independently from the optimisation technique, the optimisation of vehicle's fuel consumption starts by defining vehicle models, consisting of its longitudinal vehicle dynamics, engine and fuel consumption models. Usually, the longitudinal dynamics is modelled by second-order systems as those discussed in Section 2 for the design of low level controllers. These models are obtained by applying Newton's Second Law of motion to a vehicle, thus establishing a relation among vehicle velocity, vehicle acceleration, vehicle's tractive force and all opposing forces acting on the vehicle, with the most significant being the aerodynamic drag, rolling resistance and the gravitational force. However, additional forces can be considered to further improve model fidelity, e.g., the braking force provided by the mechanical friction brakes, retarder or exhaust brakes [119, 123] or estimated auxiliary power losses coming from the clutch or drivetrain or other auxiliary devices [123]. Once the longitudinal dynamics has been defined, it is possible to relate it to the engine speed and torque; as the tractive force is a function of the engine torque, the gear ratio and the gearbox efficiency. A gear shifting model or logic can also be added such as the work done by [119] in order to schedule the gear shifting as well as to evaluate its feasibility in relation to the engine speed and torque and additional power loss sources such as those due to engine, transmission and driveshaft rotational inertia [133]. Due to their highly nonlinear nature and parameter variation of each vehicle, fuel consumption models are obtained by interpolating experimental data. Usually they are expressed as functions of the engine speed and torque maps. However, several approaches have been used for modelling the fuel consumption functions. Linear functions with coefficients depending on the engine speed, i.e., Willans line approximation models, have been designed in [134], while a piecewise constant function have been proposed in [133] where the engine map was divided into sub-areas with a fixed fuel consumption value assigned to each zone. Polynomials are also employed, e.g., in [119] a third order polynomial function with coefficients experimentally tuned was designed. Empirical models can also be exploited, such as the Virginia Tech Comprehensive Power-Based Fuel Model (VT-CPFM) which claims to estimate fuel consumption rates with actual field measurements with a 2% error [135]. It is noted that, if Dynamic Programming (DP) or Model Predictive Control (MPC) are used to optimise fuel efficiency, no specific advantages or disadvantages were noted among the fuel consumption models. However, if the Pontryagin Maximum Principle (PMP) is adopted to compute the optimal solution, the VT-CPFM has the advantage that the derivative of the fuel consumption with respect to the engine torque still depends on that torque, thus preventing bangbang solutions where the optimal control action switches between the maximum and the minimum admissible control values [135]. Finally, the optimisation problem is completed by defining the cost function based on the fuel consumption model and constraints such as maximum accelerations and decelerations, speed limits and minimum inter-vehicular distances with respect to the preceding

vehicle, which are imposed to the longitudinal vehicle dynamics.

A common method for minimizing the cost function over the entire trip is the DP algorithm. However, this method suffers from the aforementioned “curse of dimensionality” which makes it difficult to consider the motion of the surrounding vehicles in real time, e.g., in terms of time headway with respect to the vehicle in front. Alternatively, if predictions of the accelerations of the vehicle ahead are available over a given time horizon, e.g., through V2X links, it is possible to use models of the longitudinal vehicle dynamics in Section 2 to predict its motion. The prediction of the preceding vehicle motion is then included in the optimisation of the fuel consumption of the subject vehicle as collision avoidance constraints, and MPC techniques are used to find the optimal solution over the given time horizon. However, optimisation methods that consider also the dynamics of the surrounding vehicles cannot be used for searching global optimal solutions that extend over the entire trip. They can be exploited only over a limited time horizon where prediction of the traffic motion is valid.

To overcome the aforementioned drawbacks, recently the authors in [134, 136] have focused on the design of two stages optimisation strategies which can use vehicle models with different level of accuracy for each optimisation layer. The upper level optimizes the global vehicle’s speed profile. To reduce the computational complexity in this layer simplified longitudinal vehicle dynamics and fuel consumption models are used and other road participants are not considered. Then, the low level optimiser locally adjusts the velocity profile received by the upper level over time horizons where predictions of the motion of the surrounding vehicles are available with the aim to further optimise fuel consumption while preserving road safety. It is noted that the lower layer can exploit more detailed models of the vehicle, engine and fuel consumption by considering, for instance, power losses due to the clutch, drivetrain and engine pumping losses. Moreover, the reduction of the drag force acting on the longitudinal vehicle dynamics while driving with reduced inter-vehicular distances can also be modelled in the low level optimisation stage to increase the fidelity of the vehicle dynamics and the accuracy of the optimisation. It is noted that the two stage optimisation methods are particularly suitable in a V2X environment supported by cloud computing where the cloud can be used for the upper optimisation stage while road side units, which collect real time information of the position and velocity of CAVs, can host the lower layer of the optimisation technique. Cloud assisted solutions for cooperative driving applications are also currently under investigation within the CARMA project [15].

6. Road Friction Estimation

Autonomous vehicles are equipped with various safety systems where their precise activation is highly depended on an accurate knowledge of road friction conditions (which depends on the road surface type and prevailing weather conditions). Autonomous vehicles can use several techniques involving on-board sensors, ranging from optical, acoustic, camera to tyre sensors and/or data fusion methods, to estimate the road friction. However, critical reviews, such as those reported in [137, 138], have pointed out that each technique has a limited estimation accuracy due to external noises, input frequencies, system models etc.. Furthermore, the current techniques available to autonomous vehicles estimate the instantaneous road friction coefficient and are not capable of estimating upcoming road conditions. This drawback can be mitigated if vehicles on a road segment can share their knowledge of the road condition. CAVs have the potential of improving the accuracy of the estimation as well as providing preview information of the upcoming

road segment condition via cooperative road friction estimations enabled by V2X communications. The general idea behind cooperative estimation is that every vehicle on a road section can act as a potential but imprecise sensor of road condition. Using communication systems, the road friction condition sensed by a group of vehicles on a road section can be shared and combined through data fusion algorithms to reduce the uncertainty of the estimate and increase its accuracy. Furthermore, a cooperative estimate might be stored and then distributed to multiple vehicles. Consequently, cooperation among vehicles based on V2X communication allows (in principle) a solution to the main drawbacks of current estimation methods and their application in safety systems for autonomous vehicles [139]. Moreover, conventional vehicles, which are not equipped with any road friction estimation system, can benefit from an anticipated knowledge of the road friction condition as drivers can change in advance their driving style to prevent emergency situations. For instance, V2X communications have been used by Volvo to design a system for warning vehicles about the presence of slippery spots on roads [140]. A fleet of vehicles is used to monitor the state of the road and the presence of hazardous conditions, e.g. presence of icy patches, is detected and distributed through a communication network to other road users as warnings. An example of cooperative estimation of the road friction condition was proposed in [141]. The idea behind the method is that vehicles travelling through the same road section will experience similar road conditions. Hence, when any vehicle traverses the road, its estimation can be collected and fused to the estimations calculated by vehicles passing over the same road segment to create a common and better hypothesis of the road condition. To achieve a common estimation of the road condition, the following assumptions were made: (i) the road friction coefficients are modelled as a random variable normally distributed with an unknown mean and known bounded variance, (ii) each vehicle traveling through the road section is equipped with a system for estimating the road friction coefficient, and (iii) the instantaneous estimation of the road friction for each vehicle is also normally distributed and the upper-bound for its variance is known. The road friction was modelled as a random variable to consider possible variations of this coefficient from one vehicle to another due to different types of vehicles. The authors proposed to estimate a lower bound of the friction condition such that the road friction coefficient experienced by each vehicle is above this bound with a given probability. The authors pointed out that the time to achieve satisfactory accuracy with the cooperative estimation depends on the number of participating vehicles and therefore the proportion of connected vehicles. For instance, in the case of traffic flow of 2000 vehicle/h with 10% of the vehicle participating in the common estimation process, about 13 minutes are required to re-establish a satisfactory estimation of the road condition after a sudden drop in road friction. However, a detailed analysis of converge time of the proposed algorithm in different mixing traffic scenarios is missing. Furthermore, authors did not specify the on-board road friction estimator for the implementation of the cooperative fusion technique. However, to meet the requirement of normally distributed on-board estimates, Kalman-based data fusion methods can be exploited as they guarantee that the estimation error is a Gaussian, i.e. normal, random variable. Consequently, several algorithms available in the literature, such as those presented in [142–146] can be adopted for implementing the cooperative strategy in [141]. Usually, when Kalman strategy are used, the road friction coefficient is estimated together with other measures for vehicle dynamics such as vehicle sideslip angle, wheel sideslip angles and wheel slip ratios, and forces acting on tyres. Consequently, more detailed vehicle models compared to those discussed in Sections 2 and 3 are designed for reproducing the vehicle motion while capturing tyre dynamics. For instance, in [143] the second-order nonlinear longitudinal vehicle model discussed in Section 2 is augmented with the dynamics of the wheels,

i.e., the wheel's angular velocity and the wheel's longitudinal slip, which in turn provide the longitudinal tyre force in accordance to the Pacejka model. Moreover, detailed lateral vehicle dynamics for the road friction estimation via Kalman filtering strategies has been considered in [142, 144–146]. In these works four wheel vehicle models have been designed to capture the dynamics of the yaw rate, lateral forces acting on the wheels, sideslip angles and slip ratios of the wheels, thus providing a more detailed description of the vehicle behaviour compared to that given by bicycle vehicle models discussed for lane change in Section 3.

As another example, an approach to cooperatively estimating road friction was presented in [147, 148]. The idea is to increase the precision of the estimation of the road friction coefficient available to a given fleet of vehicles that can exchange information by exploiting V2V communication channels. In the proposed framework, each vehicle in the fleet runs a dual-rate estimation scheme composed of (i) a low-level individual vehicle dynamics based estimation scheme, and (ii) an upper-level cooperative estimation scheme. The low-level individual parameter identification algorithm generates the individual high-rate estimate by using a dynamic model of the tyres and velocity based signals. The upper-level cooperative estimation scheme is fed periodically by the individual high-rate crude estimates, and it is used to converge to a common estimate among the vehicles. It is noted that, a longitudinal slip-based road friction estimation method was used as the low-level estimation system. As required by this estimation technique, a regression model of the longitudinal vehicle slips and longitudinal tyre forces, which is linear in the friction coefficient, was found and exploited to design a Least-Square (LS) identification strategy (the reader is referred to [138] for an overview of longitudinal and lateral slip-based road friction estimation methods). It is noted that, compared to Kalman filter methods, the design of slip-based strategies require less detailed vehicle dynamic models as they only focus on the estimation of the road friction coefficient rather than the entire vehicle state. However, the estimation accuracy depends on the amplitude and the frequency spectrum of the vehicle slips. For instance, the accuracy reduces for small values of the slips when the amplitude of measurement noise of wheel-speed sensors become comparable to the slip values [149]. Furthermore, LS methods might fail in case the variability of the vehicle slip profiles is not large enough (i.e., when vehicle slip profiles do not verify persistent excitation conditions) thus preventing the convergence of the LS-algorithms [147].

The effectiveness of the cooperative method in [147, 148] to improve the estimation of the road friction coefficient provided by slip-based identification techniques was proven numerically where a fleet of five vehicles was considered. A numerical investigation for different road conditions revealed that the proposed cooperative estimation can enhance the estimation of the road friction coefficient by up to 34% with respect to the case the slip-based identification method is performed by each vehicle individually and without any shared information. Furthermore, as a case study, a cooperative algorithm was employed by a collision avoidance controller to generate feasible longitudinal and lateral vehicle accelerations. The controller was then numerically tested for a scenario where the subject vehicle had to avoid two consecutive fixed obstacles. For this scenario, numerical results showed that an accurate estimation of the road friction coefficient was fundamental to avoid collisions for slippery roads. It was shown that when the low-level estimation method was used without any correction, the estimation error during the evasive manoeuvre was about 10%, but this accuracy was not sufficient to avoid a collision. On the other hand, when a cooperative approach was exploited, the residual estimation error was smaller than 3% and the vehicle could successfully perform the evasive manoeuvre. Thus, literature exists with some attempts to cooperatively estimate the road friction

coefficient for autonomous vehicles which are supported by promising numerical results. However, no experimental evidence of the effectiveness of these cooperative schemes has been provided. Furthermore, it is noted that the tyre-road friction not only depends on road conditions but also on tyre conditions. It might be interesting to see how much the tyre-road friction coefficient varies for a variety of tyres and vehicles [150]. So far it is expected that the spread is not very significant, therefore, the cooperative methods can provide at least some general warning of possible danger on the road ahead [151, 152]. However, besides tyre-road friction also the hydroplaning phenomenon should be considered. Hydroplaning might be observed as very low friction, but it is a different physical phenomenon and it strongly depends on velocity, tread depth and vehicle weight. Consequently larger differences might occur between vehicles in hydroplaning cases. Therefore ideally, besides a friction number also the road condition should be estimated and communicated between vehicles. Hence, the question of understanding if cooperative estimation of road friction is beneficial for autonomous driving scenarios is still open. As a possible approach for creating a cooperative estimate of road condition for a fleet of vehicles with large difference in the tyre-road friction coefficients, it is envisioned to augment the information available to on-board vehicle dynamics based estimation systems with environmental sensors data gathered by the fleet. Environmental sensors, such as cameras, optical and radio frequency based sensors utilise changes in the signal reflectance, polarization and absorption properties caused by the road surface. For instance, optical sensors can sense if a road is slippery by analysing how beams of light are scattered and absorbed by the road surface, while cameras can discern the road type based on pixel luminance levels. The advantage of using environmental sensors is that in principle they might provide an estimate of the road condition independently from the tyre condition and vehicle motion (e.g., they work also for stationary vehicles). Consequently, data gathered from a fleet of vehicles can be cooperatively fused and become then the input of machine learning algorithms to provide a preliminary common hypothesis on the road friction level and road condition. However, as environmental based sensors capture only road features without considering tyre dynamics, the common estimates must be further adjusted for each vehicle in the fleet with on-board sensor data to create an individual and customised estimation of the friction level. For instance, if slip-based methods are locally used, the cooperative estimate can become the initial guess of LS algorithms to improve their convergence, while if Kalman-based methods are exploited, the cooperative hypothesis on the road condition can be considered as the output of a noisy sensor of the road friction coefficient to be fused together with other on-board measurements to reduce its uncertainty. Furthermore, each vehicle might store a database containing time histories of the local friction estimate, on-board sensor readings (e.g., tyre slips and estimate tyre forces), cooperative friction estimates and environmental readings. This friction database can then be used to train machine learning techniques to predict the road friction of the upcoming road section based on the environmental sensor data of CAVs travelling on the next road segment. It is noted that the possibility of merging on-board and environmental sensor data together has been investigated for instance in [149] within the European project FRICTION. In this project, information from optical sensors, camera, tyre-sensors is fused together with the road friction estimates provided by vehicle dynamics based methods with the aim of improving the estimation accuracy. The practical benefit of an improved friction estimation was then demonstrated for the case of collision mitigation systems. On the other hand, the authors in [153] have recently proposed a machine learning based method which uses environmental sensor data for road friction predictions from a fleet of connected vehicles. The problem was formulated as a classification task to predict the friction class (slippery or non-slippery) for a sequence

of road sections. However, the output of the classifier was used only for warning and its use for CAVs applications in adverse conditions was not investigated. Hence, additional research towards the merging of approaches such as those presented in [149] and [153] are expected in the near future.

7. Conclusion

In this paper, five use-cases have been analysed with the aim investigating the potential benefits and associated limitations of connected autonomous vehicles which leverage off-board vehicle data obtained through communication channels. The use-cases analysed cover different areas of connected autonomous vehicles and common features of these use-cases are drawn below:

- V2X channels can broaden the sensory horizon of autonomous vehicles by providing additional off-board information (vehicles and features beyond the line of sight, timing of traffic lights, preview of road friction coefficient etc.). However, the achievable benefits in terms of traffic safety, fuel efficiency, and traffic flow in a connected environment depend on how this additional information is used by a vehicles control system. Therefore, control algorithms play a pivotal role in intelligently utilising V2X channels.
- In addition to a vehicle's internal states, off-board information (e.g. traffic light timing and velocity of traffic ahead) can help improve energy efficiency. Furthermore, it has been shown that fuel reduction can also be achieved by performing manoeuvres cooperatively. For instance, in the case of non-signalised intersections, vehicles can collaborate to ensure collision avoidance. In addition, cooperation also reduces the stationary wait times at signalised and non-signalised intersections which helps in reduction of fuel consumption. Similarly, cooperative techniques to equalise the velocities of vehicles over a road segment remove excessive accelerations/decelerations which result in an increase in the global fuel efficiency.
- In the case of a mixed scenario (of cooperative and non-cooperative vehicles), achievable benefits through cooperation not only depend on the control/estimation algorithms, but also on the penetration rate and the traffic scenario (e.g. traffic density, numbers of lane etc.). In addition, human driven vehicles can also benefit from the presence of connected autonomous vehicles (for instance in terms of fuel reduction). Such additional benefit is due to the intrinsic cooperation among vehicles that share the same road section.
- Although results discussed throughout the paper confirm that connected autonomous vehicles have the potential to improve traffic safety, fuel efficiency and traffic flow, most of the results have been obtained through simulation under assumptions that might be not completely fulfilled in a real environment, e.g. (i) ideal working conditions of the communication channel (e.g. no packet loss, communication failure, noise, etc.), (ii) perfect knowledge of vehicle dynamics (vehicle parameters, road friction condition etc.), (iii) perfect knowledge of the positions of the vehicles. Hence, additional investigation is required to understand how the afore-mentioned uncertainties affect cooperating driving scenarios.

Although beyond the scope of the paper, it is noted that, from a computer science prospective, cybersecurity is an active research area for connected autonomous vehicles. Information shared among CAVs in cooperative driving scenarios must be protected from cyber-attacks to guarantee road safety and privacy of CAVs and other road users.

The ongoing research on CAVs as cooperative mobile computing systems focuses to identify the cyber threats and to design strategies for preventing damages caused by such cyber-attacks. Cyber threats and attacks studied in the literature include: (a) impersonation attack (the attacker pretends to be a legitimate vehicle with the aim to send false messages); (b) message spoofing (the attacker sends false messages to spread wrong information in the network); (c) spamming attack (useless messages are spread to increase the transmission latency and bandwidth usage); (d) sybil attack (the attacker pretends to have multiple identities and act as if it were a large fleet of CAVs), and (e) message tampering (the attacker aims to drop, modify or corrupt the messages sent by legitimate vehicles to prevent other vehicles to know the original data). Requirements for cybersecurity solutions for improving trustworthiness of information source ranges from (i) authentication (vehicles must use messages transmitted only by legitimate network), (ii) non-repudiation (if required a sender must not deny a transmission of a message), to (iii) integrity (received messages are the same as the original messages and they have not been altered during the transmission). The reader is referred to recent surveys on cybersecurity for CAVs [154–157] available in the computer science literature on mobile computing for a detailed and comprehensive analysis of the cyber threats and the corresponding solutions.

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References

- [1] S. E. Shladover. Cooperative vehicle-highway automation systems. *IEEE Intelligent Transport Systems Magazine*, 1(1):10–19, 2009.
- [2] P. Thomas, A. Morris, R. Talbot, and H. Fagerlind. Identifying the causes of road crashes in Europe. *Annals of advances in automotive medicine. Association for the Advancement of Automotive Medicine. Scientific Conference*, 57:13–22, 2013.
- [3] NHTSA. Critical reasons for crashes investigated in the National Motor Vehicle Crash Causation Survey. *National Highway Traffic Safety Administration*, (Report No. DOT HS 812 115):1–2, 2015.
- [4] J. C. Ferreira, J. Almeida, and A. Rodrigues. The Impact of Driving Styles on Fuel Consumption: A Data Warehouse and Data Mining based Discovery Process. *IEEE Transactions on Intelligent Transportation Systems*, 16(5):2653–2662, 2015.
- [5] 5G-PPP. 5G Automotive Vision. <https://5g-ppp.eu/white-papers/>, 2015.
- [6] S.-W. Kim, W. Liu, M. H. Ang, E. Frazzoli, and D. Rus. The Impact of Cooperative Perception on Decision Making and Planning of Autonomous Vehicles. *IEEE Intelligent Transportation Systems Magazine*, 7(3):39–50, 2015.
- [7] A. Casavola, E. Mosca, and M. Papini. Connected and Autonomous Vehicles Introducing the future mobility. <http://www.atkinsglobal.com>, 2002.
- [8] M. During and K. Lemmer. Cooperative Maneuver Planning for Cooperative Driving. *IEEE Intelligent Transportation Systems Magazine*, 8(3):8–22, 2016.
- [9] INRIA. Cybercars 2 final report. <http://www.transport-research.info>, 2009.
- [10] SARTRE. Safe road trains for the environment; developing strategies and technologies to allow vehicle platoons to operate on normal public highways. <http://www.sartre-project.eu>, 2012.
- [11] AutoNet2030. Cooperation among vehicles with or without a driver. <http://www.autonet2030.eu/>, 2016.
- [12] UKCITE. UK Connected Intelligent Transport Environment. <https://www.ukcite.co.uk>, 2016.
- [13] I-MOTORS. i-Motors Driving Innovation. <http://www.i-motors.cloud/>, 2016.

- [14] G-ACTIVE. Green adaptive control for future interconnected vehicles. <http://g-active.uk/>.
- [15] A. Stevens, M. Dianati, K. Katsaros, C. Han, S. Fallah, C. Maple, F. McCullough, and A. Mouzakis. Cooperative automation through the cloud: The CARMA project. In *ITS European Congress*, 2017.
- [16] House of Lords Science and Technology Select Committee. Connected and Autonomous Vehicles: The future? <https://publications.parliament.uk>, 2017.
- [17] S. Kuutti, S. Fallah, K. Katsaros, M. Dianati, F. McCullough, and A. Mouzakis. A survey of the state-of-the-art localisation techniques and their potentials for autonomous vehicle applications. *IEEE Internet of Things Journal*, 5(2):829 – 846, 2018.
- [18] L. Xu, L. Wang, and G. Yin. Coordinated Control and Communication for Enhanced Safety of Highway Vehicle Platoons. In *International Conference on Connected Vehicles and Expo*, 2012.
- [19] P. A. Ioannou. *Automated Highway Systems*. Springer, 1997.
- [20] B. Van Arem, C. Van Driel, and R. Visser. The impact of cooperative adaptive cruise control on traffic-flow characteristics. *IEEE Transactions on Intelligent Transportation Systems*, 7(4):429–436, 2006.
- [21] G. M. Arnaout and J. C. Arnaout. Exploring the effects of cooperative adaptive cruise control on highway traffic flow using microscopic traffic simulation. *Transportation Planning and Technology*, 37(2):186–199, 2014.
- [22] M. Zabat, N. Stabile, S. Frascaroli, and F. Browand. The Aerodynamic Performance of Platoons A Final Report. <http://www.its.berkeley.edu>, 1995.
- [23] S. E. Shladover. PATH at 20-history and major milestones. *IEEE Transactions on Intelligent Transportation Systems*, 8(4):584–592, 2007.
- [24] A. Davila, E. Aramburu, and A. Freixas. Making the best out of aerodynamics: Platoons. In *SAE 2013 World Congress and Exhibition*, 2013.
- [25] V. Turri, B. Besselink, and K. H. Johansson. Cooperative look-ahead control for fuel-efficient and safe heavy-duty vehicle platooning. *IEEE Transactions on Control Systems Technology*, 25(1):12–28, 2017.
- [26] P. Varaiya. Smart cards on smart roads: Problems of control. *IEEE Transactions on Automatic Control*, 38(2):195–207, 1993.
- [27] R. Kianfar, P. Falcone, and J. Fredriksson. Safety verification of automated driving system. *IEEE Intelligent Transportation Systems Magazine*, 5(4):73–86, 2013.
- [28] C. Nowakowski, J. O’Connell, S. E. Shladover, and D. Cody. Cooperative Adaptive Cruise Control: Driver Acceptance of Following Gap Settings Less than One Second. In *Human Factors and Ergonomics Society 54th Annual Meeting*, pages 2033–2037, 2010.
- [29] D. Swaroop, J.K. Hedrick, C. C. Chien, and P. Ioannou. A Comparison of Spacing and Headway Control Laws for Automatically Controlled Vehicles. *Vehicle System Dynamics*, 23(1):597–625, 1994.
- [30] R. Rajamani. *Vehicle dynamics and control*. Springer, 2012.
- [31] H. Hao and P. Barooah. Stability and robustness of large platoons of vehicles with doubleintegrator models and nearest neighbor interaction. *International Journal of Robust and Nonlinear Control*, 23(18):2097–2122, 2013.
- [32] Y. Zheng, S. E. Li, J. Wang, D. Cao, and K. Li. Stability and scalability of homogeneous vehicular platoon: Study on the influence of information flow topologies. *IEEE Transactions on Intelligent Transportation Systems*, 17(1):14–26, 2016.
- [33] G. J. L. Naus, R. P. A. Vugts, J. Ploeg, M. J. G. van de Molengraft, and M. Steinbuch. String-stable CACC design and experimental validation: A frequency-domain approach. *IEEE Transactions on Vehicular Technology*, 59(9):4268–4279, 2010.
- [34] M. Treiber and A. Kesting. *Traffic Flow Dynamics: Data, Models and Simulation*. Springer, 2013.
- [35] L. Xiao and F. Gao. Practical string stability of platoon of adaptive cruise control vehicles. *IEEE Transactions on Intelligent Transportation Systems*, 12(4):1184–1194, 2011.
- [36] V. Milanés and S.E. Shladover. Handling Cut-In Vehicles in Strings of Cooperative Adaptive Cruise Control Vehicles. *Journal of Intelligent Transportation Systems*, 20(2):178–191, 2016.
- [37] P. Seiler, A. Pant, and K. Hedrick. IEEE Transactions on Automatic Control. *Vehicle System Dynamics*, 49(10):1835–1841, 2004.
- [38] E. Shaw and J. K. Hedrick. String stability analysis for heterogeneous vehicle strings. In *American Control Conference*, pages 3118–3125, 2007.
- [39] J. Ploeg, N. Van De Wouw, and H. Nijmeijer. Fault tolerance of cooperative vehicle platoons subject to communication delay. In *IFAC Workshop on Time Delay Systems*, pages 352–357, 2015.
- [40] J. C. Zegers, E. Semsar-Kazeroni, J. Ploeg, N. van de Wouw, and H. Nijmeijer. Consensus

- control for vehicular platooning with velocity constraints. *IEEE Transactions on Control System Technology*, 2017.
- [41] D. Jia Dongyao and D. Ngoduy. Enhanced cooperative car-following traffic model with the combination of V2V and V2I communication. *Transportation Research Part B: Methodological*, 90:172–191, 2016.
- [42] S. E. Li, Y. Zheng, K. Li, and L. Wang. An Overview of Vehicular Platoon Control under the Four-Component Framework. In *IEEE Intelligent Vehicles Symposium*, pages 286–291, 2015.
- [43] U. Montanaro, M. Tufo, Fiengo, M. di Bernardo, and S. Santini. On convergence and robustness of the extended cooperative cruise control. In *Conference on Decision and Control*, pages 4083–4088, 2014.
- [44] J. C. Gerdes and J. K. Hedrick. Vehicle speed and spacing control via coordinated throttle and brake actuation. *Control Engineering Practice*, 5(11):1607–1614, 1997.
- [45] S. E. Li, F. Gao, D. Cao, and K. Li. Multiple-model switching control of vehicle longitudinal dynamics for platoon-level automation. *IEEE Transactions on Vehicular Technology*, 65(6):4480–4492, 2016.
- [46] F. Lin, M. Fardad, and M. R. Jovanovic. Optimal control of vehicular formations with nearest neighbor interactions. *IEEE Transactions on Automatic Control*, 57(9):2203–2218, 2012.
- [47] J.-W. Kwon and D. Chwa. Adaptive bidirectional platoon control using a coupled sliding mode control method. *IEEE Transactions on Intelligent Transportation Systems*, 15(5):2040–2048, 2014.
- [48] A. A. Peters, R. H. Middleton, and O. Mason. Leader tracking in homogeneous vehicle platoons with broadcast delays. *Automatica*, 50(1):64–74, 2014.
- [49] U. Montanaro, M. Tufo, Fiengo, and S. Santini. A novel cooperative adaptive cruise control approach: Theory and hardware in the loop experimental validation. In *Mediterranean Conference on Control and Automation*, pages 37–42, 2014.
- [50] Y. Zheng, S. E. Li, K. Li, F. Borrelli, and J. K. Hedrick. Distributed model predictive control for heterogeneous vehicle platoons under unidirectional topologies. *IEEE Transactions on Control Systems Technology*, 25(3):899–910, 2017.
- [51] S. E. Shladover, D. Su, and X.-Y. Lu. Impacts of cooperative adaptive cruise control on freeway traffic flow. *Journal of the Transportation Research*, 2324:63–70, 2012.
- [52] S. Konduri, P. R. Pagilla, and S. Darbha. Vehicle platooning with multiple vehicle look-ahead information. In *IFAC World Congress*, pages 5768–5773, 2017.
- [53] Y. Zheng, S. E. Li, K. Li, and L.-Y. Wang. Stability margin improvement of vehicular platoon considering undirected topology and asymmetric control. *IEEE Transactions on Control Systems Technology*, 24(4):1253–1265, 2016.
- [54] Y. Wu, S. E. Li, Y. Zheng, and J. K. Hedrick. Distributed sliding mode control for multi-vehicle systems with positive definite topologies. In *Conference on Decision and Control*, pages 5213–5219, 2016.
- [55] A. M. H. Al-Jhayyish and K. W. Schmidt. Feedforward strategies for cooperative adaptive cruise control in heterogeneous vehicle strings. *IEEE Transactions on Intelligent Transportation Systems*, 19(1):113–122, 2018.
- [56] U. Montanaro, G. Fiengo, A. Tufano, and S. Santini. On the effectiveness of the extended cooperative adaptive control for vehicles platooning. In *European Control Conference*, pages 2453–2458, 2016.
- [57] F. Gao, S. E. Li, Y. Zheng, and D. Kum. Robust control of heterogeneous vehicular platoon with uncertain dynamics and communication delay. *IET Intelligent Transport Systems*, 10(7):503–513, 2016.
- [58] F. Gao, D. F. Dang, S. S. Huang, and S. E. Li. Decoupled robust control of vehicular platoon with identical controller and rigid information flow. *International Journal of Automotive Technology*, 18(1):157–164, 2017.
- [59] Y. A Harfouch, S. Yuan, and S. Baldi. Adaptive control of interconnected networked systems with application to heterogeneous platooning. In *International Conference on Control and Automation*, pages 212–217, 2017.
- [60] R. Rajamani, H. S. Tan, B. Law, and W.-B. Zhang. Demonstration of integrated longitudinal and lateral control for the operation of automated vehicles in platoons. *IET Intelligent Transport Systems*, 8:695–708, 2000.
- [61] E. H. M. Lim and J. K. Hedrick. Lateral and longitudinal vehicle control coupling for automated vehicle operation. In *American Control Conference*, pages 3676–3680, 1999.
- [62] A. Sasoh and T. Ohara. Shock wave relation containing lane change source term for two-lane traffic flow. *Journal of the Physical Society of Japan*, 71(9):23392347, 2002.

- [63] Center for Urban Transportation Research University of South Florida. Impact of Automated Vehicles on Highway Safety and Operations. 2013.
- [64] S. Moridpour, G. Rose, and M. Sarvi. Effect of Surrounding Traffic Characteristics on Lane Changing Behavior. *Journal of Transportation Engineering*, 136(11):973–985, 2010.
- [65] M. Ardelt, C. Coester, and N. Kaempchen. Highly automated driving on freeways in real traffic using a probabilistic framework. *IEEE Transactions on Intelligent Transportation Systems*, 13(4):1576–1585, 2012.
- [66] S. Ulbrich and M. Maurer. Situation Assessment in Tactical Lane Change Behavior Planning for Automated Vehicles. In *IEEE Conference on Intelligent Transportation Systems*, volume 2015-October, pages 975–981, 2015.
- [67] M. A. S. Kamal, S. Taguchi, and T. Yoshimura. Efficient vehicle driving on multi-lane roads using model predictive control under a connected vehicle environment. In *IEEE Intelligent Vehicles Symposium, Proceedings*, pages 736–741, 2015.
- [68] M. A. S. Kamal, S. Taguchi, and T. Yoshimura. Efficient Driving on Multilane Roads under a Connected Vehicle Environment. *IEEE Transactions on Intelligent Transportation Systems*, 17(9):2541–2551, 2016.
- [69] T. Dao, C. M. Clark, and J. P. Huissoon. Distributed platoon assignment and lane selection for traffic flow optimization. In *Intelligent Vehicles Symposium*, pages 739–744, 2008.
- [70] T. Dao. *A Decentralized Approach to Dynamic Collaborative Driving Coordination*. PhD thesis, University of Waterloo, 2008.
- [71] Q. Jin, G. Wu, K. Boriboonsomsin, and M. Barth. Improving traffic operations using real-time optimal lane selection with connected vehicle technology. In *Intelligent Vehicles Symposium*, pages 70–75, 2014.
- [72] R. P. Roess and E. S. Prassas. *The Highway Capacity Manual: A Conceptual and Research History*. Springer, 2014.
- [73] V. Milanés, D. F. Llorca, J. Villagrà, J. Pérez, C. Fernández, I. Parra, C. González, and M. A. Sotelo. Intelligent automatic overtaking system using vision for vehicle detection. *Expert Systems with Applications*, 39(3):3362–3373, 2012.
- [74] S. Dixit, S. Fallah, U. Montanaro, M. Dianati, A. Stevens, F. McCullough, and A. Mouzakitis. Trajectory planning and tracking for autonomous overtaking: State-of-the-art and future prospects. *Annual Reviews in Control*, DOI: 10.1016/j.arcontrol.2018.02.001, in press, 2018.
- [75] B. Kim, D. Kim, S. Park, Y. Jung, and K. Yi. Automated Complex Urban Driving based on Enhanced Environment Representation with GPS/map, Radar, Lidar and Vision. In *IFAC Symposium on Advances in Automotive Control*, pages 190–195, 2016.
- [76] S. Kitazawa. Control Target Algorithm for Direction Control of Autonomous Vehicles in Consideration of Mutual Accordance in Mixed Traffic Conditions. In *International Symposium on Advanced Vehicle Control 2016*, 2016.
- [77] J. E. Naranjo, C. González, R. García, and T. De Pedro. Lane-change fuzzy control in autonomous vehicles for the overtaking maneuver. *IEEE Transactions on Intelligent Transportation Systems*, 9(3):438–450, 2008.
- [78] Y. Gao, A. Gray, J. V. Frasc, T. Lin, E. Tseng, J. K. Hedrick, and F. Borrelli. Spatial Predictive Control for Agile Semi-Autonomous Ground Vehicles. In *International Symposium on Advanced Vehicle Control*, 2012.
- [79] J. Nilsson, Y. Gao, A. Carvalho, and F. Borrelli. Manoeuvre generation and control for automated highway driving. In *IFAC World Congress*, pages 6301–6306, 2014.
- [80] S. Glaser, B. Vanholme, S. Mammari, D. Gruyer, and L. Nouvelière. Maneuver-based trajectory planning for highly autonomous vehicles on real road with traffic and driver interaction. *IEEE Transactions on Intelligent Transportation Systems*, 11(3):589–606, 2010.
- [81] N. H. Amer, Hairi Zamzuri, K. Hudha, and Z. A. Kadir. Modelling and Control Strategies in Path Tracking Control for Autonomous Ground Vehicles : A Review of State of the Art and Challenges. *Journal of Intelligent & Robotic Systems*, 86(2):225–254, 2016.
- [82] C. Katrakazas, M. Quddus, W. Chen, and L. Deka. Real-time motion planning methods for autonomous on-road driving: State-of-the-art and future research directions. *Transportation Research Part C: Emerging Technologies*, 60:416–442, 2015.
- [83] C. Kim, M. Kim, and K. Lee. Development of a Full Speed Range Path-following System for the Autonomous Vehicle. In *International Conference on Control, Automation and Systems*, pages 710–715, 2015.
- [84] D. Filev, J. Lu, and D. Hrovat. Future Mobility: Integrating Vehicle Control With Cloud Computing. *Mechanical Engineering*, 135(3):18–24, 2013.

- [85] J. Kong, M. Pfeiffer, G. Schilbach, and F. Borrelli. Kinematic and Dynamic Vehicle Models for Autonomous Driving Control Design. In *IEEE Intelligent Vehicles Symposium*, pages 1094–1099, 2015.
- [86] C. M. Kang, S. H. Lee, and C.C. Chung. Comparative evaluation of dynamic and kinematic vehicle models. In *IEEE Conference on Decision and Control*, pages 648–653, 2014.
- [87] J. M. Snider. Automatic Steering Methods for Autonomous Automobile Path Tracking. *Robotics Institute, Pittsburgh, PA, Tech. Rep. CMU-RITR-09-08*, 2009.
- [88] A. Sorniotti, P. Barber, and S. De Pinto. Path Tracking for Automated Driving: A Tutorial on Control System Formulations and Ongoing Research. In *Automated Driving: Safer and More Efficient Future Driving*, pages 71–140. 2017.
- [89] A. Rupp and M. Stolz. Survey on Control Schemes for Automated Driving on Highways. In *Automated Driving*, pages 43–69. 2017.
- [90] NHTSA. National motor vehicle crash causation survey. *U.S. Department of Transportation, National Highway Traffic Safety Administration*, 2008.
- [91] European Commission. Traffic Safety Basic Facts: Junction. <https://ec.europa.eu>, 2016.
- [92] J.M. Rios-Torres and A. A. Malikopoulos. A Survey on Coordination of Connected and Automated Vehicles at Intersections and Merging at Highway On-Ramps. *IEEE Transactions on Intelligent Transportation Systems*, 18(5):1066 – 1077, 2017.
- [93] L. Chen and C. Englund. Cooperative Intersection Management: A Survey. *IEEE Transactions on Intelligent Transportation Systems*, 17(2):570–586, 2016.
- [94] M. Lebre, F. Mouël, E. Ménard, A. Garnault, B. Bradai, and V. Picron. Real scenario and simulations on GLOSA traffic light system for reduced CO2 emissions, waiting time and travel time. In *ITS World Congress*, 2015.
- [95] K. Katsaros, R. Kernchen, M. Dianati, and D. Rieck. Performance study of a Green Light Optimal Speed Advisory (GLOSA) Application Using an Integrated Cooperative ITS Simulation Platform. In *International Wireless Communications and Mobile Computing Conference*, pages 918–923, 2011.
- [96] M. Seredynski, B. Dorransoro, and D. Khadraoui. Comparison of Green Light Optimal Speed Advisory approaches. In *IEEE Conference on Intelligent Transportation Systems*, pages 2187–2192, 2013.
- [97] N. Wan, A. Vahidi, and A. Luckow. Optimal speed advisory for connected vehicles in arterial roads and the impact on mixed traffic. *Transportation Research Part C: Emerging Technologies*, 69:548–563, 2016.
- [98] G. Mahler and A. Vahidi. An optimal velocity-planning scheme for vehicle energy efficiency through probabilistic prediction of traffic-signal timing. *IEEE Transactions on Intelligent Transportation Systems*, 15(6):2516–2523, 2014.
- [99] G. Mahler and A. Vahidi. Reducing idling at red lights based on probabilistic prediction of traffic signal timings. In *American Control Conference*, pages 6557 – 6562, 2012.
- [100] M. A. S. Kamal, J. Imura, A. Ohata, T. Hayakawa, and K. Aihara. Control of Traffic Signals in a Model Predictive Control Framework. In *IFAC Symposium on Control in Transportation Systems*, pages 38–43, 2012.
- [101] M. A. S. Kamal, J. Imura, T. Hayakawa, A. Ohata, and K. Aihara. Traffic Signal Control of a Road Network Using MILP in the MPC Framework. *International Journal of Intelligent Transportation Systems Research*, 13(2):107–118, 2015.
- [102] H. Yang, H. Rakha, and M. V. Ala. Eco-Cooperative Adaptive Cruise Control at Signalized Intersections Considering Queue Effects. *IEEE Transactions on Intelligent Transportation Systems*, 18(6):1–11, 2016.
- [103] B. HomChaudhuri, A. Vahidi, and P. Pisu. A fuel economic model predictive control strategy for a group of connected vehicles in urban roads. In *American Control Conference*, pages 2741–2746, 2015.
- [104] B. HomChaudhuri, A. Vahidi, and P. Pisu. Fast Model Predictive Control-Based Fuel Efficient Control Strategy for a Group of Connected Vehicles in Urban Road Conditions. *IEEE Transactions on Control Systems Technology*, 25(2):760–767, 2017.
- [105] R. Hult, G. R. Campos, E. Steinmetz, L. Hammarstrand, P. Falcone, and H. Wymeersch. Coordination of Cooperative Autonomous Vehicles. *IEEE Signal Processing Magazine*, 33(6):74–84, 2016.
- [106] K. Dresner and P. Stone. Multiagent traffic management: a reservation-based intersection control mechanism. In *International Joint Conference on Autonomous Agents and Multiagent Systems*, pages 530–537, 2004.

- [107] S. Huang, A. W. Sadek, and Y. Zhao. Assessing the Mobility and Environmental Benefits of Reservation-Based Intelligent Intersections Using an Integrated Simulator. *IEEE Transactions on Intelligent Transportation Systems*, 13(3):1201–1214, 2012.
- [108] K. Dresnert and P. Stone. Multiagent traffic management: An improved intersection control mechanism. In *International Joint Conference on Autonomous Agents and Multiagent System*, pages 471–477, 2005.
- [109] K. Dresner and P. Stone. A Multiagent Approach to Autonomous Intersection Management. *Journal of artificial intelligence research*, 31:591–656, 2008.
- [110] I. A. Zohdy and H. A. Rakha. Intersection Management via Vehicle Connectivity: The Intersection Cooperative Adaptive Cruise Control System Concept. *Journal of Intelligent Transportation Systems*, 20(1):17–32, 2016.
- [111] I. H. Zohdy, R. K. Kamalanathsharma, and H. Rakha. Intersection management for autonomous vehicles using iCACC. In *IEEE Conference on Intelligent Transportation Systems*, pages 1109–1114, 2012.
- [112] J. Lee and B. Park. Development and evaluation of a cooperative vehicle intersection control algorithm under the connected vehicles environment. *IEEE Transactions on Intelligent Transportation Systems*, 13(1):81–90, 2012.
- [113] M. A. S. Kamal, J. Imura, A. Ohata, T. Hayakawa, and K. Aihara. Coordination of automated vehicles at a traffic-lightless intersection. In *IEEE Conference on Intelligent Transportation Systems*, pages 922–927, 2013.
- [114] R. Hult, G. R. Campos, P. Falcone, and H. Wymeersch. An approximate solution to the optimal coordination problem for autonomous vehicles at intersections. In *American Control Conference*, pages 763–768, 2015.
- [115] U.S. Energy Information Administration. Study of the Potential Energy Consumption Impacts of Connected and Automated Vehicles. www.eia.gov, 2017.
- [116] C. Zhang. *Predictive Energy Management in Connected Vehicles: Utilizing Route Information Preview for Energy Saving*. PhD thesis, Clemson University, 2010.
- [117] M. Ansarey, M. Shariat Panahi, H. Ziarati, and M. Mahjoob. Optimal energy management in a dual-storage fuel-cell hybrid vehicle using multi-dimensional dynamic programming. *Journal of Power Sources*, 250:359–371, 2014.
- [118] R. Bellman. *Dynamic Programming*. Princeton, 1957.
- [119] E. Ozatay, S. Onori, J. Wollaeger, U. Ozguner, G. Rizzoni, D. Filev, J. Micheline, and S. Di Cairano. Cloud-based velocity profile optimization for everyday driving: A dynamic-programming-based solution. *IEEE Transactions on Intelligent Transportation Systems*, 15(6):2491–2505, 2014.
- [120] C. Qiu, H. Shen, A. Sarker, V. Soundararaj, M. Devine, A. Rindos, and E. Ford. Towards green transportation: Fast vehicle velocity optimization for fuel efficiency. In *International Conference on Cloud Computing Technology and Science*, pages 59–66.
- [121] B. Asadi and A. Vahidi. Predictive cruise control: Utilizing upcoming traffic signal information for improving fuel economy and reducing trip time. *IEEE Transactions on Control Systems Technology*, 19(3):707–714, 2011.
- [122] B. Németh, A. Csikós, I. Varga, and P. Gáspár. Design of platoon velocity based on multi-criteria optimization. In *IFAC Symposium on Robust Control Design*, pages 523–528, 2012.
- [123] N. Murgovski, B. Egardt, and M. Nilsson. Cooperative energy management of automated vehicles. *Control Engineering Practice*, 57:84 – 98, 2016.
- [124] I. Johansson, J. Jin, X. Ma, and H. Pettersson. Look-ahead speed planning for heavy-duty vehicle platoons using traffic information. *Transportation Research Procedia*, 22:561–569, 2017.
- [125] G. Wu and Z. Dong. Design, analysis and modeling of a novel hybrid powertrain system based on hybridized automated manual transmission. *Mechanical Systems and Signal Processing*, 93:688–705, 2017.
- [126] A. Sciarretta and L. Guzzella. Control of hybrid electric vehicles. *IEEE Control Systems Magazine*, 27(2):60–70, 2007.
- [127] M. Ehsani, Y. Gao, and A. Emadi. *Modern Electric, Hybrid Electric, and Fuel Cell Vehicles: Fundamentals, Theory, and Design*. CRC Press, 2009.
- [128] C. Sun, S. J. Moura, X. Hu, J. K. Hedrick, and F. Sun. Dynamic Traffic Feedback Data Enabled Energy Management in Plug-in Hybrid Electric Vehicles. *IEEE Transactions on Control Systems Technology*, 23(3):1075–1086, 2015.
- [129] J. C. Herrera, D. B. Work, R. Herring, X. Ban, Q. Jacobson, and A. M. Bayen. Evaluation of traffic data obtained via GPS-enabled mobile phones: The Mobile Century field experiment. *Transportation Research Part C: Emerging Technologies*, 18(4):568–583, 2010.

- [130] C. M. Martnez, D. Cao X. Hu, E. Velenis, B. Gao, and M. Wellers. Energy management in plug-in hybrid electric vehicles: Recent progress and a connected vehicles perspective. *IEEE Transactions on Vehicular Technology*, 66:4534–4549, 2017.
- [131] A. A. Malikopoulos. Supervisory Power Management Control Algorithms for Hybrid Electric Vehicles: A Survey. *IEEE Transactions on Intelligent Transportation Systems*, 15(5):1869–1885, 2014.
- [132] Y. Huang, H. Wang, A. Khajepour, H. He, and J. Ji. Model predictive control power management strategies for HEVs: A review. *Journal of Power Sources*, 341:91–106, 2017.
- [133] Q. Cheng, L. Nouvelire, and O. Orfila. A new eco-driving assistance system for a light vehicle: Energy management and speed optimization. In *IEEE Intelligent Vehicles Symposium*, pages 1434–1439, 2013.
- [134] H. Lim, C. C. Mi, and W. Su. A distance-based two-stage ecological driving system using an estimation of distribution algorithm and model predictive control. *IEEE Transactions on Vehicular Technology*, 66(8):6663–6675, Aug 2017.
- [135] H. A. Rakha, K. Ahn, K. Moran, B. Saerens, and E. Van den Bulck. Virginia tech comprehensive power-based fuel consumption model: Model development and testing. *Transportation Research Part D: Transport and Environment*, 16(7):492 – 503, 2011.
- [136] H. Lim, W. Su, and C. C. Mi. Distance-based ecological driving scheme using a two-stage hierarchy for long-term optimization and short-term adaptation. *IEEE Transactions on Vehicular Technology*, 66(3):1940–1949, March 2017.
- [137] S. Muller, M. Uchanski, and K. Hedrick. Estimation of the Maximum Tire-Road Friction Coefficient. *Journal of Dynamic Systems, Measurement, and Control*, 125(4):607, 2003.
- [138] R. Rajamani, N. Piyabongkarn, J. Lew, K. Yi, and G. Phanomchoeng. Tire-road friction-coefficient estimation. *IEEE Control Systems Magazine*, 30(4):54–69, 2010.
- [139] F. Gustafsson. Automotive Safety Systems. *IEEE Signal Processing Systems*, 26(4):32–47, 2009.
- [140] Volvo. Volvo Cars puts 1000 test cars to use: Scandinavian cloud-based project for sharing road-condition information becomes a reality. <https://www.media.volvocars.com>, 2014.
- [141] S. Müller, M. Uchanski, and J. K. Hedrick. Cooperative estimation using vehicle communications. *Vehicle System Dynamics*, 39(2):121–133, 2003.
- [142] S. Antonov, A. Fehn, and A. Kugi. Unscented kalman filter for vehicle state estimation. *Vehicle System Dynamics*, 49(9):1497–1520, 2011.
- [143] K. Enisz, D. Fodor, I. Szalay, and G. Kohlrusz. Improvement of active safety systems by the extended kalman filter based estimation of tire-road friction coefficient. In *IEEE International Electric Vehicle Conference*, 2014.
- [144] Y. Xu, B. Deng, and G. Xu. Estimation of vehicle states and road friction based on DEKF. In *International Conference on Power Electronics Systems and Applications*, 2015.
- [145] Q. Cheng, A. Correa-Victorino, and A. Charar. A new nonlinear observer using unscented kalman filter to estimate sideslip angle, lateral tire road forces and tire road friction coefficient. In *IEEE Intelligent Vehicles Symposium*, pages 709–714, 2011.
- [146] L. Chen, M. Bian, Y. Luo, and K. Li. Estimation of road-tire friction with unscented kalman filter and mse-weighted fusion based on a modified dugoff tire model. In *SAE World Congress and Exhibition*, 2015.
- [147] M. Jalalmaab, M. Pirani, B. Fidan, and S. Jeon. Cooperative Least Square Parameter Identification by Consensus within the Network of Autonomous Vehicles. In *SAE International Journal of Passenger Cars - Electronic and Electrical Systems*, pages 255–261, 2016.
- [148] M. Jalalmaab, M. Pirani, B. Fidan, and S. Jeon. Cooperative road condition estimation for an adaptive model predictive collision avoidance control strategy. In *Intelligent Vehicles Symposium*, pages 1072–1077, 2016.
- [149] Sami Koskinen. *Sensor Data Fusion Based Estimation of Tyre Road Friction to Enhance Collision Avoidance*. PhD thesis, Technical Research Centre of Finland, 2010.
- [150] H. Pacejka. *Tire and Vehicle Dynamics*. Butterworth-Heinemann, 2005.
- [151] J. Prokes. Realtime estimation of tyre-road friction for vehicle state estimator. *MSc Thesis, Chalmers University*, 2015.
- [152] Michelin. The tyre, grip. *Société de Technologie Michelin*, 2001.
- [153] G. Panahandeh, E. Ek, and N. Mohammadiha. Road friction estimation for connected vehicles using supervised machine learning. In *IEEE Intelligent Vehicles Symposium*, 2017.
- [154] B. Mokhtar and M. Azab. Survey on security issues in vehicular ad hoc networks. *Alexandria Engineering Journal*, 54(4):1115–1126, 2015.
- [155] J. Petit and S. E. Shladover. Potential cyberattacks on automated vehicles. *IEEE Transactions*

- on Intelligent Transportation Systems*, 16(2):546–556, 2015.
- [156] Q. He, X. Meng, and R. Qu. Survey on cyber security of cav. In *Forum on Cooperative Positioning and Service Survey*, 2017.
- [157] G. De La Torre, P. Rad, and K.-K. R. Choob. Driverless vehicle security: Challenges and future research opportunities. *Future Generation Computer System*, 2018, in press.