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# A platoon based cooperative eco-driving model for mixed automated and human-driven vehicles at a signalised intersection

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## Abstract

The advancements in communication and sensing technologies can be exploited to assist the drivers in making better decisions. In this paper, we consider the design of a real-time cooperative eco-driving strategy for a group of vehicles with mixed automated vehicles (AVs) and human-driven vehicles (HVs). The lead vehicles in the platoon can receive the signal phase and timing information via vehicle-to-infrastructure (V2I) communication and the traffic state of preceding vehicle and current platoon via vehicle-to-vehicle (V2V) communication. We propose a receding horizon model predictive control (MPC) method to minimise the fuel consumption for platoons and drive the platoons to pass the intersection on a green phase. The method is then extended to dynamic platoon splitting and merging rules for cooperation among AVs and HVs in response to the high variation in urban traffic flow. Extensive simulation tests are also conducted to demonstrate the performance of the model in various conditions in the mixed traffic flow and different penetration rates of AVs. Our model shows that the cooperation between AVs and HVs can further smooth out the trajectory of the latter and reduce the fuel consumption of the entire traffic system, especially for the low penetration of AVs. It is noteworthy that the proposed model does not compromise the traffic efficiency and the driving comfort while achieving the eco-driving strategy.

*Keywords:* Cooperative driving, Platoon based operations, Eco-driving, Automated vehicles, Heterogeneous flow, Car following model

## 1. Introduction

Transportation is one of the main sources of energy consumption and greenhouse gas emission. In the EU, transportation is responsible for 33% of energy consumption and 23% of total emissions (European Commission, 2016). Road transport represents most of it, 72.8% in total greenhouse gas emissions and 73.4% in transport energy demand. A lot of work has been done to mitigate these effects from different aspects, for example, optimised engine design,

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better road surface condition and more training for drivers. Due to the continually increasing number of vehicles, however, the total vehicle fuel consumption is still rising. The concept of "eco-driving" has drawn increasing attention from both researchers and government (Carsten et al., 2016). The core of eco-driving technologies is to provide drivers with a variety of advice and feedback to minimise the fuel consumption and emissions while driving.

Unlike continuous traffic flow on freeways, traffic flows on urban roads are regularly interrupted by traffic signals and conflicting traffic flows at intersections. As such the vehicles travel with strong variations in their velocity and consume more fuel. Eco-driving strategies can be designed to reduce the idling time on the red light and subsequent strong acceleration by advising the drivers to approach intersections using a moderate acceleration and deceleration. The development of sensing and communication technologies make Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) communication possible in the near future. These technologies offer potential applications for eco-driving patterns at intersections as the connected vehicles can receive the Signal Phase and Timing (SPaT) information from the intersection controller by V2I and also receive the position and velocity information from surrounding vehicles by V2V communication. Better speed advice can be generated using this information, and thus vehicles may adjust their speed in advance, in order to avoid stopping at the stop line and subsequent strong acceleration, and consequently reduce the fuel consumption.

Both field experiments (Schall and Mohnen, 2017) and simulator experiments (Van der Voort et al., 2001; Staubach et al., 2014) show that eco-driving reduces the fuel consumption between 5% and 18%, and drivers exhibit a high acceptance towards an eco-driving support system. It has no negative effects on safety, but many eco-driving methods lead to low travel speed and may have a negative impact on the following vehicles (Wu et al., 2015; Staubach et al., 2014). Moreover, they may even increase the travel time of the host vehicles and following vehicles.

This paper proposes a real-time cooperative eco-driving strategy for a platoon including mixed automated vehicles (AVs) and human-driven vehicles (HVs) approaching a signalised intersection. It adopts a model predictive control (MPC) method to control the trajectories of AVs. Here the AVs are considered the leaders of the platoon with the aim of minimising the total fuel consumption of the whole platoon without sacrificing the travel time of the leaders. It also reduces the travel time for the following vehicles to a certain extent. The rest of the paper is organised as follows: the literature review of the eco-driving modelling is presented in section 2. Then, the proposed model structure, optimisation method, and platoon control scheme are described in section 3. In section 4, the properties of the proposed model are extensively studied and the performance of the proposed method for different penetration rates of AVs is also examined. A final section 5 summarises the paper's findings.

## 2. Literature Review

One of the applications of speed advisory systems is Intelligent Speed Adaptation (ISA) which is widely used in several EU countries (Almqvist et al., 1991; Liu and Tate, 2004). ISA devices are primarily aimed at safer driving by advising drivers a desired speed and speed limits on specific road sections (Ngoduy et al., 2009). Experiments showed that ISA strategies can potentially mitigate congestion and reduce fuel consumption and pollutant emissions due to smoother speed variations (Oei and Polak, 2002; Panis et al., 2006). In conventional ISA systems, vehicles are still driven by humans, and traffic information is usually obtained from loop detectors.

There are two main methods proposed in the literature which utilise the traffic signal information to reduce idle time and fuel consumption. The first approach suggests a constant speed or constant acceleration for an individual driver to reduce the idle time or fuel consumption. This is commonly named Green Light Optimised Speed Advisory (GLOSA) system. It is usually implemented as an optimisation model by assuming a simple speed pattern in front of the intersection. Rakha and Kamalanathsharma (2011) considered a fuel consumption model in the objective function and showed that simplified objective functions such as minimising the deceleration or idling time may not get the optimal result in terms of fuel consumption. This work is further extended to control the variable speed limit for each vehicle to minimise the fuel consumption (Kamalanathsharma et al., 2015) and integrate queue estimation (Yang et al., 2017). Mandava et al. (2009) developed an arterial velocity planning algorithm which provided speed advice to the drivers regarding the most fuel optimal path computed using upcoming signal information. The objective function was aimed at minimising the deceleration and acceleration rates, and 12-14% energy/emission savings were achieved. Tielert et al. (2010) conducted a large-scale simulation to identify the impact of gear choice and distance to the intersection. They found that sub-optimal gear choice can reduce the positive performance of the speed adaptation. Another finding was that the benefit of providing information to the vehicles located further than 600m is negligible. Treiber and Kesting (2014) implemented three strategies of speed adaptation: early break, early start and avoiding queue in the Improved Intelligent-Driver Model. The travel time decreases linearly with the penetration of equipped vehicles. They also found that increasing the maximum speed from 50km/h to 70km/h doubles the performance index. Katwijk and Gabriel (2015) considered the impact of different trajectories on the fuel consumption. The vehicle was advised to use a smaller deceleration, even combined with a period of constant speed, instead of a hard deceleration in front of the red light. Stebbins et al. (2017) developed a method to suggest an acceleration to the leading vehicle only in a platoon to reduce delays. It was assumed that every vehicle that is the first to pass the intersection on a green light can be selected as a leading vehicle. Instead of controlling the speed directly, Ubiergo and Jin (2016) proposed a green driving strategy to control the individual advisory speed limit of connected vehicles while following their leaders at signalised intersections; it can be applied to any level of market penetration. Although no fuel consumption model was explicitly used in this modelling method, it still saved 15% in travel delays and 8% in fuel consumption and emission.

The second approach uses an optimal control or an MPC method to provide dynamic or real-time speed advice to an individual vehicle considering the local and predictive traffic states. This approach is thus more suitable for AVs because of the real-time detecting and speed adjustment. Asadi and Vahidi (2011) calculated the optimal speed that reduces idling at red lights using the given future state of traffic lights and developed an optimisation-based MPC model to consider multiple objectives. Kamal et al. (2013) predicted the dynamics of the preceding vehicle based on the information from inter-vehicle communication and considered the signal status of the upcoming intersections to compute the optimal vehicle control input for fuel economy by an MPC method. He et al. (2015) developed a multi-stage optimal control model considering the spatial and temporal constraints by the queue in front of the intersection. They also considered the constraints to reduce the negative impact on the following vehicles, but it was only active at the terminal time step at each stage. Wan et al. (2016) used optimal control theory to solve the minimum fuel control problem and found that the minimal fuel driving strategy is a bang-singular-bang control, which means either maximum acceleration or engine shut down is used. By employing a sub-optimal method, the speed advisory equipped vehicle can also benefit the following conventional vehicles. De Nunzio et al. (2016) used a combination of a pruning algorithm and shortest path method to find the minimum energy consumption path in multi-intersections. The non-convex optimal control problem was then reduced to a convex problem which can be solved efficiently.

To the best of our knowledge, most current work focuses on developing fuel economic control strategies for a single vehicle without considering the impact on the other vehicles. HomChaudhuri et al. (2017) considered neighbourhood information exchange and designed a decentralised control model emulating the selfish behaviour of human drivers, but their model still considers one vehicle and does not describe the interactions between platoons. Zhou et al. (2017); Ma et al. (2017) proposed a parsimonious shooting heuristic algorithm to optimise the trajectories of a stream of vehicles and considered multiple objective functions such as fuel consumption and travel time, but all vehicles are required to be AVs in their method. Jiang et al. (2017) proposed an eco-driving model in partially connected and automated vehicles environment; however, they did not consider the cooperation of AVs and HVs, even though the behaviour of the AV still affects the following vehicles. This indicates that there are no platoon-based dynamics in their approach. Our model will fill in this gap by showing that the cooperation between AVs and HVs can further smooth the trajectory of the latter and consequently reduce the fuel consumption of the whole platoon. The proposed method will optimise the fuel consumption for platoons and drive the platoons to pass the intersection on a green phase. The proposed model is flexible that allows multiple AVs and HVs in the platoon. Both the impact of cooperation among AVs and cooperation among AVs and HVs will be studied in detail. Most existing work uses the rolling horizon MPC method, and the optimised vehicles sometimes travel with low speed to achieve a better fuel economy. In this paper, a distinctive receding horizon MPC method is proposed to ensure that eco-driving strategies do not have an adverse impact on the traffic efficiency. On the contrary, the proposed model can increase the speed while passing the intersection and thus increase the traffic efficiency. In addition, the driving comfort is considered by using jerk as the control variable.

## Notation

The notation in Table 1 is used throughout this paper.

## 3. Problem formulation

This paper focuses on the design of an eco-driving strategy for a group of vehicles with mixed AVs and HVs. The movements of HVs are modelled by a car-following model while the dynamics of AVs are described by an MPC method. For the sake of simplicity, in this paper, an optimal velocity model (OVM) is applied to describe the behaviour of HVs (Bando et al.,

Table 1: Notation of major variables used in this paper

| Symbol | Description |
|---|---|
| $t$ | Time instant |
| $x_i^a(t), v_i^a(t), a_i^a(t)$ | The position, speed, acceleration of an AV $i$ at time $t$ where the superscript $a$ denotes AV |
| $x_j^h(t), v_j^h(t), a_j^h(t)$ | The position, speed, acceleration of an HV $j$ at time $t$ where the superscript $h$ denotes HV |
| $\hat{x}_{tf}, \hat{v}_{tf}, \hat{a}_{tf}$ | The desired position, speed, acceleration at terminal time, respectively where subscript $tf$ denotes terminal time |
| $u(t)$ | The jerk of an AV which is the control variable at time $t$ |
| $J$ | Total cost in the MPC objective function |
| $L$ | Running cost in the MPC objective function |
| $\theta$ | Terminal cost in the MPC objective function |
| $F_i^a(t), F_j^h(t)$ | Instantaneous fuel consumption rate for AV $i$, and HV $j$, respectively, at time $t$ |
| $t_i^f$ | Terminal time for the vehicle $i$ and also the time to pass the stop line |
| $T_k^g, T_k^r$ | The start time of green light, red light respectively, in cycle $k$ |

1995). Nevertheless, the proposed modelling methodology holds for any other car-following model. Our method allows several closely running vehicles to form a platoon and pass the intersection on the green light without stopping. A basic schematic representation is shown in Figure 1.

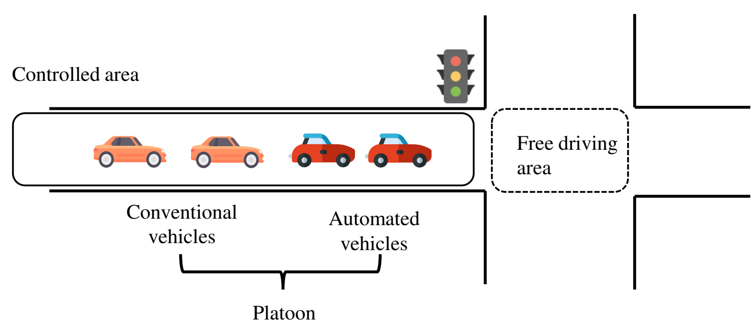



Figure 1: Schematic of eco-driving problem at a signalised intersection

### 3.1. Assumptions

To facilitate our model development, some necessary assumptions are made as follows.

1. In order to set up the cooperative behaviour between the AVs and the following HVs, AVs have to know the positions and speeds of some following vehicles and the direct preceding vehicle in real time. We will assume that this information is available through either connected vehicle technology or a roadside unit (RSU) (Jia and Ngoduy, 2016a). This assumption will be relaxed in section 4.3 where the AVs obtain this information about the direct following vehicle via its own detectors.
2. All AVs can receive the signal timing information from the downstream intersection via V2I.

3. No communication delay or detection error is considered in the paper; for cooperative driving behaviour in a platoon with realistic communication, we refer to Jia and Ngoduy (2016b). This assumption will be relaxed in our future work.
4. AVs in different platoons can share the information about the vehicles' arrival time via either V2V or RSU; hence they can predict a better arrival time.
5. This work only focuses on the longitudinal movement on the urban road.

It is worth noticing that AVs will interact with the downstream intersection and decide their dynamics to get the whole platoon through the intersection during the green time period.

### *3.2. Optimal velocity model*

The OVM is formulated based on the presumption that a vehicle is driven to reach an optimal velocity, which depends on the headway with respect to the preceding vehicle in a continuous time step. The acceleration of vehicle in the OVM is calculated by

$$a_j^h(t) = \kappa \left[V_{op}(\Delta x_j(t)) - v_j^h(t)\right] \tag{1}$$

where $\Delta x_j(t) = x_{j-1}(t) - x_j^h(t)$ is the distance headway between vehicles $j$ and its preceding vehicle $j-1$. $V_{op}(\Delta x_j(t))$ defines the optimal velocity, which is a function of the distance headway. $\kappa$ is the sensitivity. The sensitivity is the inverse of the delay time that is required to reach the optimal velocity. In this paper, the following velocity function proposed by Helbing and Tilch (1998) is chosen:

$$V_{op}\left(\Delta x_j\right) = V_1 + V_2 \tanh\left[C_1(\Delta x_j - l_c) - C_2\right] \tag{2}$$

where $V_1, V_2, C_1, C_2$ are the parameters and $l_c$ denotes the vehicle length. The parameters calibrated by the empirical follow-the-leader data for city traffic in Helbing and Tilch (1998) are used in this paper: $\kappa = 0.85\,\mathrm{s}^{-1}, V_1 = 6.75\,\mathrm{m/s}, V_2 = 7.91\,\mathrm{m/s}, C_1 = 0.13\,\mathrm{m}^{-1}, C_2 = 1.57$ and $l_c = 5\,\mathrm{m}$. Because the OVM may generate unrealistic high acceleration (Helbing and Tilch, 1998), the acceleration limits shown in Table 2 are applied.

### *3.3. Model predictive control*

Each AV is able to receive real-time information from the preceding vehicle and following vehicles via V2V, such as position and velocity. In the MPC method, a common assumption is that the preceding vehicle is travelling at a constant velocity. So the time for the AV to arrive at the intersection on green time can also be estimated. Then a receding horizon MPC method will be used. For the safety and comfort purposes, a further assumption is made that the AV travels across the intersection with a constant velocity, which implies that the acceleration of the AV at the stop line should be 0. Accordingly, in our model, the control variable is the derivative of the acceleration of the AV, which is also called "jerk" and denoted as $u(t)$.

*3.3.1. State variables*

In order to minimise the fuel consumption for all vehicles in the platoon, the state variables of those vehicles are included in the system state. For a general platoon including $m$ AVs and $n$ HVs, its state is designed as

$$\mathbf{X}(t) = [\underbrace{x_i^a(t), v_i^a(t), a_i^a(t), \cdots, x_m^a(t), v_m^a(t), a_m^a(t)}_{\text{AVs}}, \underbrace{x_j^h(t), v_j^h(t), \cdots, x_n^h(t), v_n^h(t)}_{\text{HVs}}]^T$$
$$i = 1, \cdots, m;\ j = 1, \cdots, n \quad (3)$$

The corresponding system dynamic function is

$$\dot{\mathbf{X}}(t) = [\underbrace{v_i^a(t), a_i^a(t), u_i^a(t), \cdots, v_m^a(t), a_m^a(t), u_m^a(t)}_{\text{AVs}}, \underbrace{v_j^h(t), a_j^h(t), \cdots, v_n^h(t), a_n^h(t)}_{\text{HVs}}]^T \quad (4)$$

where the acceleration of the HV $a_j^h(t)$ is calculated by equation 1.

*3.3.2. Objective function*

The total cost function for the platoon is defined as:

$$\min_u J = \theta(\mathbf{X}(\mathbf{t^f})) + \int_{t_i^0}^{t_i^f} L(\mathbf{X}(t))dt \quad (5)$$

The control goal is to drive AVs from the current position to the stop line with the desired velocity and acceleration. Therefore, the terminal cost is designed as the squared difference between the terminal state for the AVs and the desired terminal state:

$$\theta(\mathbf{X}(\mathbf{t^f})) = \sum_i^m p_1(x_i^a(t_i^f) - \hat{x}_{tf})^2 + p_2(v_i^a(t_i^f) - \hat{v}_{tf})^2 + p_3(a_i^a(t_i^f) - \hat{a}_{tf})^2 \quad (6)$$

where $p_1,\ p_2,\ p_3$ are the weights for the corresponding terms. In the paper, the desired terminal position $\hat{x}_{tf}$ is the downstream stop line, and the desired terminal speed $\hat{v}_{tf}$ is the maximum allowed velocity which is 14.66 m/s. Note that the maximum speed of the AVs is the same as that of HVs using the described parameters. The desired terminal acceleration $\hat{a}_{tf}$ is $0\,\mathrm{m/s^2}$ because of the constant velocity assumption described above.

The running cost is the driving cost at every time step. In this paper, it means the total fuel consumption for all vehicles in the platoon and it is formulated as:

$$L(\mathbf{X}(t)) = \sum_i^m F_i^a(t) + \sum_j^n F_j^h(t) \quad (7)$$

An instantaneous fuel consumption model developed by Akcelik (1989) is adopted in this work. It uses the instantaneous acceleration and velocity to estimate the fuel consumption rate:

$$F = \alpha + \beta_1 P_T + (\beta_2 m a^2 v)_{a>0} \quad (8)$$

where $P_T$ is the total power (kW) required to drive the vehicle, which is the sum of coast-down drag power, inertia power and extra engine power. $P_T$ is non-negative. The third term means extra engine drag power during acceleration, which only exists when the acceleration is larger than zero.

$$P_T = \max\{0, d_1 v + d_2 v^2 + d_3 v^3 + mav\} \tag{9}$$

The parameters $\alpha,\ \beta_1,\ \beta_2,\ d_1,\ d_2,\ d_3,\ m$ in equations 8 and 9 are taken from Akcelik (1989) and are $\alpha = 0.666\,\mathrm{mL/s}$, $\beta_1 = 0.072\mathrm{mL/kJ}$, $\beta_2 = 0.0344\mathrm{mL/(kJ \cdot m/s^2)}$, $d_1 = 0.269\mathrm{kN}$, $d_2 = 0.0171\mathrm{kN/(m/s)}$, $d_3 = 0.000672\mathrm{kN/(m/s)^2}$, $m = 1680\,\mathrm{kg}$.

The terminal time $t_i^f$ is set to be the earliest time that allows the AV $i$ to pass the intersection on the green phase. It is calculated by

$$t_i^f = \max(t_i^{f'}, t_i^g) \tag{10}$$

where $t_i^{f'}$ denotes the earliest possible arrival time, and is calculated by

$$t_i^{f'} = \max(t_i^{min}, t_{i-1}^f + h) \tag{11}$$

where $t_i^{min}$ denotes the minimum travel time by using the highest jerk, $t_{i-1}^f$ denotes the travel time of the preceding vehicle $i-1$. If the vehicle $i-1$ is an AV, its estimated travel time information can be available via V2V. If it is an HV that belongs to the preceding platoon, the AV (or AVs) in the preceding platoon must have the travel time information and transfer to vehicle $i$. If not, it can be estimated by using loop detectors (Treiber and Kesting, 2014; Guler et al., 2014; He et al., 2015) or connected vehicles (Yang et al., 2017; Zheng and Liu, 2017). $h$ denotes the safety time headway of an AV with its preceding vehicle. Please note that it is the same as the saturation time headway of HVs using the described parameters. This is specially designed to show that the reduction of travel time is not resulting from the smaller time headway of AVs, but from the proposed eco-driving method. $t_i^g$ denotes the start of the green light which is closest to $t_i^{f'}$. It is calculated by

$$t_i^g = \begin{cases} T_k^g & t_i^{f'} \in [T_k^g, T_k^r) \\ T_{k+1}^g & t_i^{f'} \in \left[T_k^r, T_{k+1}^g\right] \end{cases} \tag{12}$$

where $T_k^g (T_k^r)$ denotes the start time of green (red) light in the signal cycle $k$.

Please note that when there are multiple AVs in a platoon, they have different $t_i^0$ and $t_i^f$ and the proposed optimal control problem is a multi-stage optimal control problem which can be solved by GPOPS. We only discuss isolated intersection in this paper, but the proposed model can be extended to multi-intersections without much trouble by taking each intersection as a stage (He et al., 2015).

#### *3.3.3. Constraints*

$$\textbf{Speed constraints: } v_{min} \le v_i^a(t) \le v_{max} \tag{13a}$$

$$\textbf{Acceleration constraints: } a_{min} \le a_i^a(t) \le a_{max} \tag{13b}$$

$$\textbf{Jerk constraints: } u_{min} \le u_i^a(t) \le u_{max} \tag{13c}$$

$$\textbf{Safety constraints: } a_i^a(t) \le a_i^{OVM}(t) \tag{13d}$$

where $v_{min}$, $v_{max}$, $a_{min}$, $a_{max}$, $u_{min}$, $u_{max}$ denote the lower and upper bounds of the velocity, acceleration and jerk, respectively. The same speed and acceleration limits in Table 2 are used for both MPC and OVM. $a_i^{OVM}(t)$ is calculated by equation 1 using the speed and the gap of AV. This implies that the car-following model (i.e. OVM) is used as the upper bound of the acceleration for an AV. It prevents the MPC algorithm from acting too aggressively to achieve the final goal. So basically, the upper bound of the acceleration reads: $a_i^a(t) \leq min(a_{max}, a_i^{OVM}(t))$. It also provides the possibility of handing over to human driving more smoothly if required.

### *3.4. Interactions between AVs and HVs*

In order to provide an eco-driving strategy for the benefits of both AVs and HVs in the platoon, several kinds of cooperation are considered in the model. The overall interactions are shown in Figure 2. Note that in the platoon, HVs are modelled by the OVM and AVs are controlled by the MPC method.

In Figure 2, there are basically two types of cooperative behaviour for AVs: (1) interacting with preceding vehicles between platoons; (2) interacting with the AVs or HVs within the platoon. If the preceding vehicle belongs to the preceding platoon, then the leading (automated) vehicle of the preceding platoon knows the passing time of its members and can transfer the information to the AVs in the considered platoon. Otherwise, the AVs have to predict the arrival time of the preceding vehicles based on the data acquired by their built-in detectors or other sources of communication such as RSU or even connected vehicle technologies. For the vehicles in a platoon, the cooperation is designed for the purposes of safety and fuel efficiency. The AVs in the platoon consider the dynamics of all vehicles in the platoon and attempt to find a strategy that minimises the fuel consumption for all vehicles in the platoon.

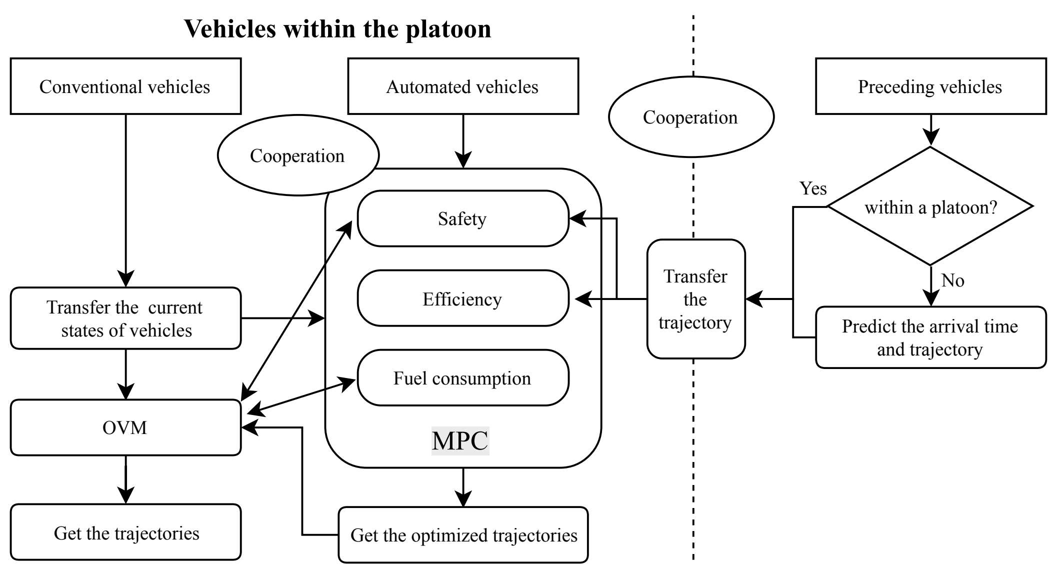



Figure 2: Interactions between AVs and HVs

### 3.5. The control framework for platoons

The proposed method is applied to a platoon instead of a single vehicle, so how to define the platoon and how to manage the platoon dynamically are key challenges in this paper. The platoon is usually defined as a group of vehicles that are adjacent to each other and have similar traffic state (see Ngoduy (2013); Jia and Ngoduy (2016a,b) and references therein). On an urban road, some vehicles can pass through the intersection on a green light and travel with the speed that depends on the traffic conditions. Other vehicles have to stop at the stop line when the traffic signal turns red. So it is natural to define the platoon as the group of vehicles that can pass on the same green phase.

There are two criteria for a platoon:

1. All the vehicles in a platoon must pass the intersection on the same green phase.
2. The leading vehicle in a platoon must be an AV, and all AVs can only be located in front of the HVs in each platoon.

Criterion 2 is essential for the proposed eco-driving method. This is because only when the AV is in front of the HV, it can affect the following vehicles' movements by controlling its own jerk. The platoon in this paper is different from the controversial one. It is heterogeneous that may include AVs and HVs. The purpose of a platoon is to allow cooperation among AVs and HVs to reduce the total fuel consumption which pass the intersection on the same green phase. The platoon dynamics including splitting and merging are to determine which vehicle should be considered in the cooperation loop. The setting of a platoon is not to ensure all the vehicles in the platoon can pass the intersection on the same green phase. In fact, the vehicles can pass the intersection on the same green phase is the necessary condition to form a platoon, rather than the result. Different platoon settings in mixed traffic flow will be discussed in detail in section 4.2.

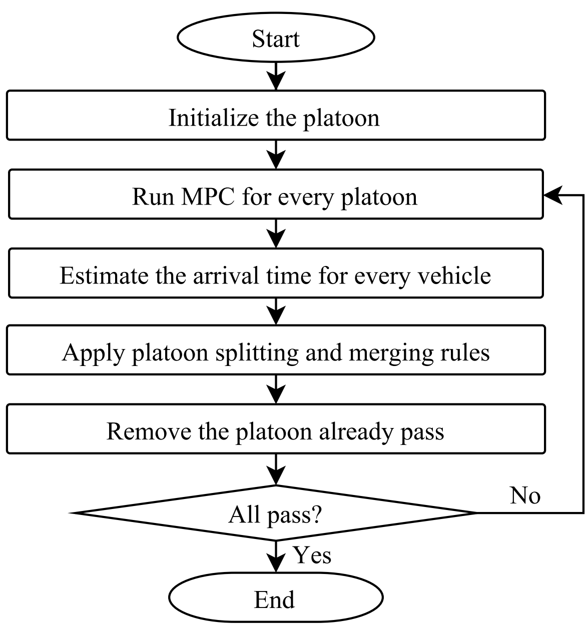



Figure 3: The overall control framework

The control framework for platoon dynamics is shown in Figure 3 and the main processes are described as follows:

1. Split all the vehicles on the road into several groups according to the maximum allowed number of vehicles in a platoon, and the leading AV (or AVs) in a platoon becomes the host vehicle.
2. Run the MPC algorithm for every platoon, the optimised control variables are only applied to the host vehicles for the next time step, while the behaviour of all other vehicles is governed by the OVM.
3. Apply the platoon split and merge rules every $T_1$ time steps which is $z$ times of the control update time step T (i.e. $T_1 = zT$).

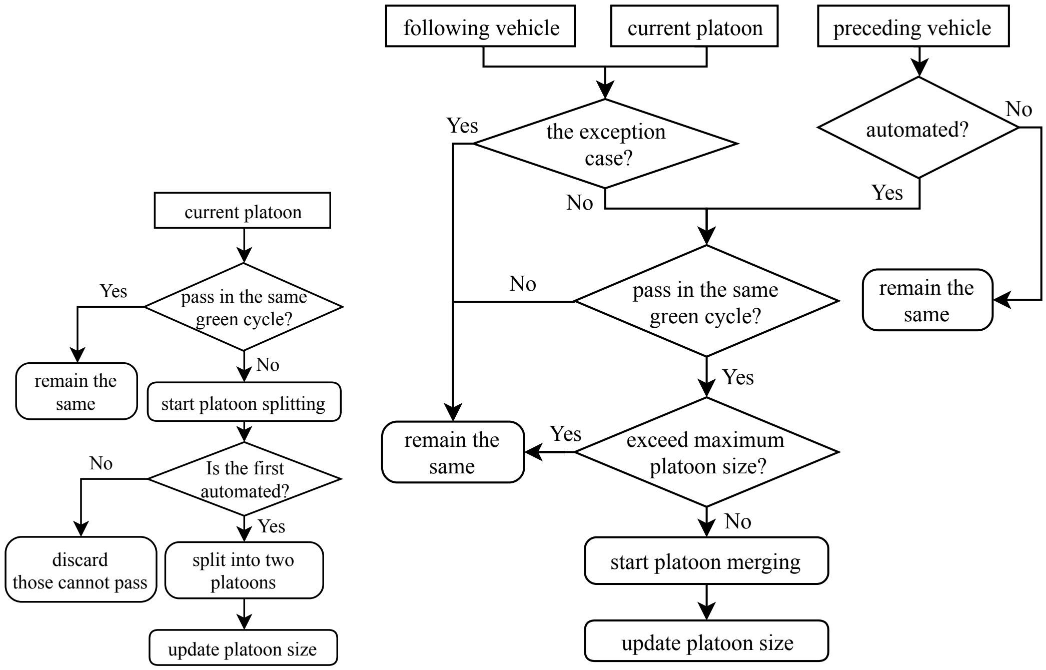
The platoon splitting and merging rules mainly consider the planned vehicle arrival time, signal timing information, and the defined minimum and maximum number of vehicles in a platoon. The rules are described in the following.

1. Splitting rule (see Figure 4a): After the MPC optimisation is executed, some of the vehicles in the platoon may not pass the intersection on the green time. Then the splitting rule applies. If the first vehicle that cannot pass on the same green light is an AV, then it is split from the original platoon and becomes the leading vehicle for the new platoon. Otherwise, all those that cannot pass on the same green light are discarded by the current platoon.
2. Merging rule (see Figure 4b): Merging rule is more complicated than the splitting rule as it may operate in two directions: merge with the preceding vehicles or the following vehicles. In both cases, it needs to check whether the two key criteria are still satisfied after merging. The exceptional case in figure 4b means an AV follows an HV. Please note that merging with the preceding vehicles has higher priority than merging with the following vehicles as the operations of the preceding vehicle can affect all the following vehicles and may get better performance.

The splitting rule is always applied before the merging rule. The discarded vehicles by the splitting rule will try to find a chance to form another platoon by the merging rule where every AV can be seen as a separate platoon with size 1. This does not mean that every HV must belong to a platoon. If an HV does not belong to any platoon, it may have to stop in front of the stop line.

### 3.6. Gauss pseudospectral method

A Matlab software package GPOPS (Rao et al., 2010) is used to solve the proposed optimal control problem. It mainly uses a numerical method, namely Gauss pseudospectral method, and is widely used in trajectory planning problems for vehicles (Wu et al., 2015; He et al., 2015) and trains (Ye and Liu, 2016). The method belongs to a direct approach (Stryk and Bulirsch, 1992) whose main idea is transforming the optimal control problem into a nonlinear programming (NLP) problem, which can then be solved by a variety of well-known solvers such as SNOPT (Gill et al., 2005) used in GPOPS. The performance of GPOPS strongly depends on the parameter settings (Ye and Liu, 2016). Usually, the user needs to try several combinations of parameter settings to find the best suitable ones. The key parameters used in GPOPS and the model are listed in Table 2.




(a) Platoon splitting (b) Platoon merging

Figure 4: Platoon splitting and merging framework

## 4. Numerical studies

### 4.1. Properties of terminal cost

The terminal cost has three terms in equation 6. The first term forces the vehicle to arrive at the intersection at the terminal time. The second term maximises the speed entering the intersection. We will show that this can increase the capacity of the intersection. The third term allows the vehicle to pass the intersection with a constant speed which is the maximum speed resulting from the second term. This mainly concerns the safety when crossing the intersection. If this term were removed, the acceleration of vehicle would drop to zero suddenly due to the speed limit after the terminal time (Ntousakis et al., 2016).

In this study, three scenarios are considered to illustrate the benefits of the proposed terminal cost settings. The simulation scenario considered in this paper is a single lane road with a traffic signal light at location 250 m ahead. We consider 10 vehicles driving on the road and attempting to cross the intersection. At the beginning of the simulation, all vehicles have the same velocity of 10 m/s and acceleration of 0 m/s$^2$. The other parameters used in the MPC method are shown in Table 2.

- Scenario T1: no speed advice is given to the drivers and the accelerations of all vehicles are only calculated by the OVM. We will call this case as OVM for simplicity.
- Scenario T2: the first vehicle is an AV and only the first term in the terminal cost function 6 is considered while the running cost remains the same in function 7.
- Scenario T3: the first vehicle is an AV and the terminal cost and running cost are the same as function 6 and 7, respectively.

Table 2: The parameters in the proposed eco-driving method

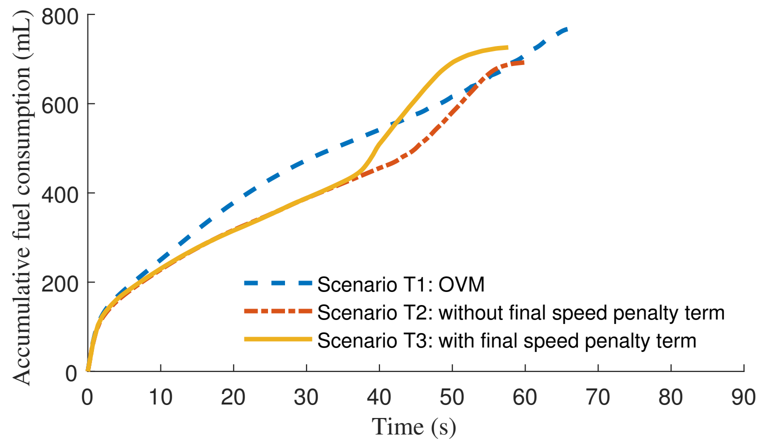
| Parameter settings in GPOPS | | |
|---|---|---|
| Parameter | Description | Value |
| setup.autoscale | Whether the optimal control problem is scaled automatically | ‘on’ |
| setup.derivatives | Method to compute the derivatives of the objective function (gradient) and the constraints for NLP solver | ‘complex’ |
| setup.tolerances | Optimality and feasibility tolerances for the NLP solver | [1e-3, 2e-3] |
| limits.meshPoints | Locations of mesh points in the initial run | [-1,1] |
| limits.nodesPerInterval | Number of allowable collocation points in a mesh interval | $2*(t^f - t^0)$ |
| setup.mesh.tolerance | Mesh refinement tolerance | 1e-4 |
| setup.mesh.iteration | Mesh refinement iterations to perform | 8 |

| Parameter settings in model | | | |
|---|---|---|---|
| Parameter | Description | Value | Unit |
| $T_M$ | Sample time for MPC method | 0.5 | s |
| $T_O$ | Sample time for OVM | 0.1 | s |
| $h$ | Safety time headway for an AV | 2 | s |
| $p_1$ | Penalty weight for position difference | $10^5$ | |
| $p_2$ | Penalty weight for velocity difference | $10^6$ | |
| $p_3$ | Penalty weight for acceleration difference | $10^7$ | |
| $v_{max}$ | Maximum speed | 14.66 | m/s |
| $v_{min}$ | Minimum speed | 0 | m/s |
| $a_{max}$ | Maximum acceleration | 3 | m/s$^2$ |
| $a_{min}$ | Minimum acceleration | $-6$ | m/s$^2$ |
| $u_{max}$ | Maximum jerk (limit for the control variable) | 4 | m/s$^3$ |
| $u_{min}$ | Minimum jerk (limit for the control variable) | $-4$ | m/s$^3$ |

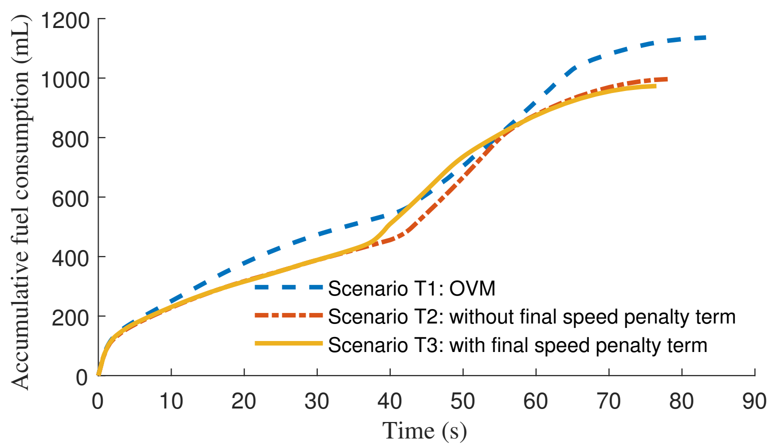
When all vehicles have crossed the stop line, the total fuel consumption is shown in figure 5a. As expected, the fuel consumption of vehicles under MPC is much less than that in OVM. More specifically, scenario T2 reduces by 9.7% and scenario T3 reduces by 5.2% compared with scenario T1. Due to the stop in front of the intersection on red light, it also takes much more time to discharge the ten vehicles.

In the two scenarios of the optimal control, the model with terminal speed and acceleration penalty consumes 1.7 % more fuel, as the vehicles need to accelerate more. Moreover, it also needs less green time to discharge the vehicles. The detailed data can be seen in Table 3. It takes them 20.2 s and 18s in the green time window to pass in scenario T2 and scenario T3, respectively. This means that scenario T3 can let one more vehicle pass in the same signal settings. Thus, scenario T3 increases the capacity by 11.1 % compared with scenario T2 and by 44.4 % compared with scenario T1.

Figure 6 shows the detailed position and speed trajectory for every vehicle in the three scenarios. It can be seen that vehicles in both scenarios T2 and T3 can pass the intersection without stopping due to the guidance of the first vehicle. They also have a much higher final speed than vehicles in scenario T1, in which vehicles have to accelerate from a complete stop.




(a)



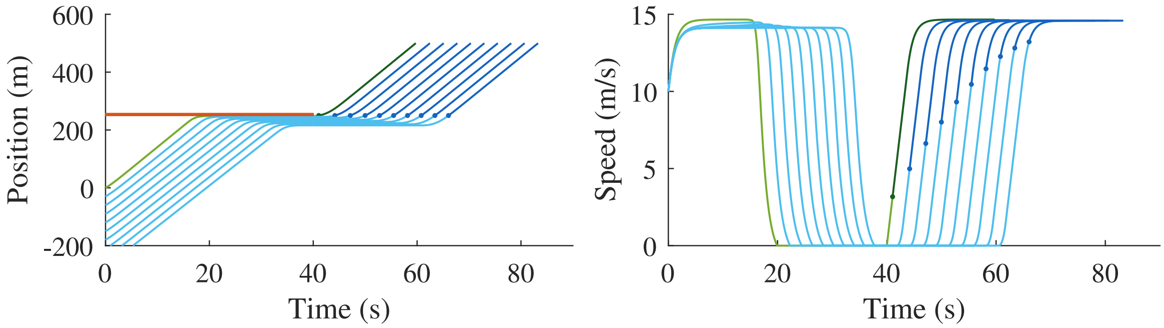

(b)

Figure 5: Accumulative fuel consumption (a) when all the vehicles arrive at the stop line; (b) when all the vehicles arrive at the extended distance.

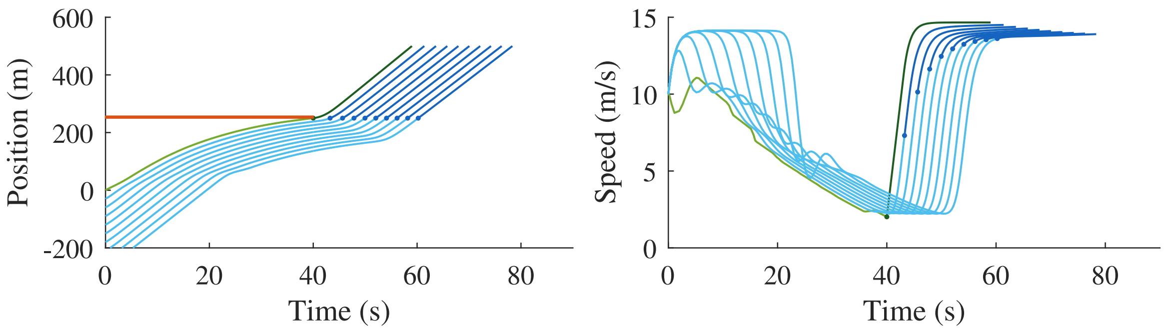
Table 3: Simulation results with different terminal costs

| Scenario | Terminal position | Total fuel consumption (mL) | Used green time (s) | Total travel time (s) |
|---|---|---|---|---|
| scenario T1 | stop line | 767.1 | 25.8 | 527.7 |
| | extended | 1136.4 | | 716.05 |
| scenario T2 | stop line | 693.0 (-9.7%) | 20.2 (-21.7%) | 507.0 (-3.9%) |
| | extended | 996.8 (-12.3%) | | 688.9 (-3.8%) |
| scenario T3 | stop line | 726.9 (-5.2%) | 18.0 (-30.2%) | 491.2 (-6.9%) |
| | extended | 973.2 (-14.4%) | | 670.1 (-6.4%) |

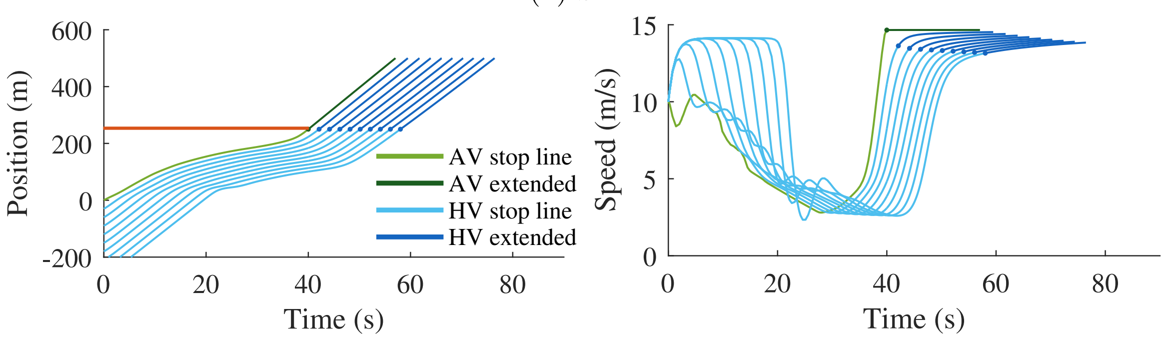
The speed of the first vehicle in scenario T2 is always decreasing while that in scenario T3 decreases first and then increases to the maximum speed, which is the desired final speed. This also explains why scenario T3 uses more fuel than scenario T2. It is consistent with figure 5a. The total fuel consumption of scenario T2 and T3 are almost identical in the first 35s. Because of the high terminal speed cost in the scenario T3, the vehicles consume much




(a) Scenario T1




(b) Scenario T2




(c) Scenario T3

Figure 6: State trajectories of all vehicles with different terminal costs under three scenarios

more fuel to accelerate.

The terminal speed of vehicles in scenario T3 is much higher than that in scenario T1 and T2 which is the main reason that it consumes more fuel than scenario T2. This also indicates that the vehicles in the Scenario T3 will consume much less fuel in the future. To better understand the impact of different terminal costs, we let the vehicles keep running for another 250m and achieve similar terminal speed. The vehicles in scenario T1 accelerate to maximum speed quickly, but only the first vehicle in scenario T2 and T3 can achieve the maximum speed, the following vehicles have slightly slower speed. The scenario T3 consumes the least fuel and has the least total travel time as shown in Fig. 5b which mainly benefit from the high terminal speed at the stop line. Thus, we conclude that the proposed terminal cost function is a good choice for eco-driving in terms of the local benefit and future benefit.

### 4.2. Properties of the running cost

A major feature in the proposed model is that the leading AVs consider the benefits of both themselves and the following vehicles, but the impact of this type of cooperation is still not clear. Three typical cases in the mixed traffic flow are considered in the following simulation studies. Only 4 vehicles will be considered in the simulations, and the platoon setting in each case is shown in Figure 7. To facilitate the following discussion, two major time points are defined. Let $t_1$ denote the time when the first vehicle arrives at the stop line and $t_2$ denote the time when the 4th vehicle arrives at the stop line. In this section, $t_1$ is the start time of green light and also the time when the first AV passes the stop line, which is 40 s. Two measurements are considered here: (i) The accumulated fuel consumption during 0s and $t_1$; (ii) The accumulated fuel consumption during 0s and $t_2$ on the studied link. Let $M_1$ and $M_2$ denote these two measurements, respectively.

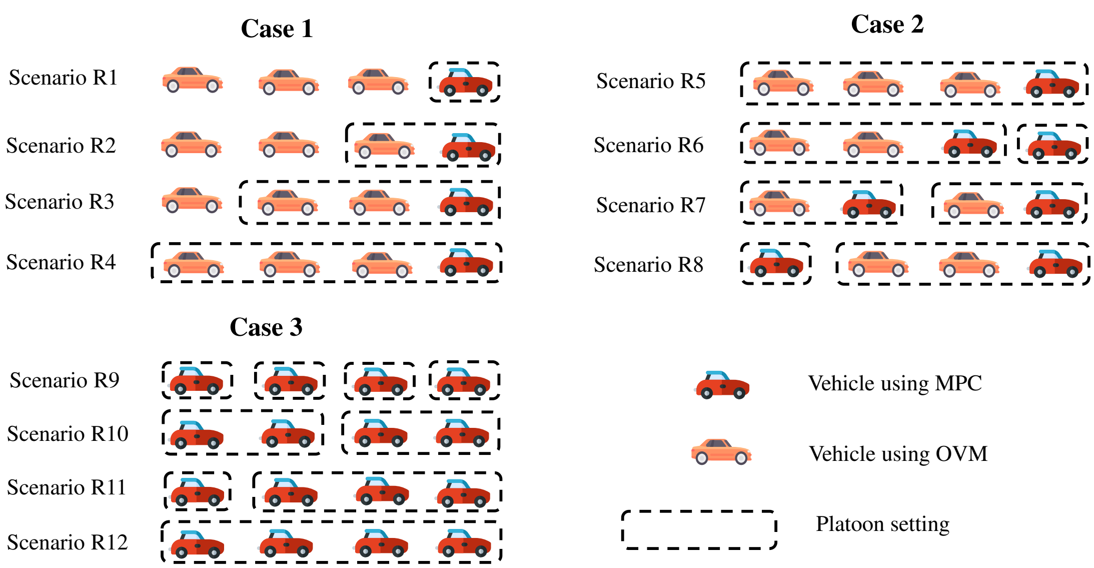



Figure 7: Platoon settings for running cost simulations

#### 4.2.1. Case 1: an AV is followed by HVs

When an AV is followed by several HVs, the question is whether the AV should consider the movements of the following vehicles, and what benefits this cooperation can bring. To this end, four scenarios are considered in this case. In the simulations, the first vehicle is an AV, and the following three vehicles are HVs.

- Scenario R1: The running cost of the host vehicle is its own fuel consumption.
- Scenario R2: The running cost of the host vehicle is the sum of its own and first following vehicle's fuel consumption.
- Scenario R3: The running cost of the host vehicle is the sum of its own and first two following vehicles' fuel consumption. 11
- Scenario R4: The running cost of the host vehicle is the sum of its own and all three following vehicles' fuel consumption.

The fuel consumption for each scenario is shown in Table 4, and the state trajectories are shown in Figure 8. In Table 4, the data are organised in the form of "$M_1/M_2$" in each cell. The bold items mean they come from AVs, and the same style will be applied in the ensuing paper. Please note that in this case, the optimisation is only performed during 0s and 40s and in the remaining period vehicles are driven by the OVM. It can be seen that the more HVs are considered in the platoon, the less total fuel consumption with $M_1$ results. The reduction is as high as 7.3 % in scenario R4 where there are three following vehicles in the platoon. At the same time, the first vehicle consumes more fuel than in the scenarios where there are fewer vehicles in the platoon. This is due to the fact that the AV has to modify its trajectory to change the following vehicles' behaviour. This can also be seen in Figure 8. As the leading vehicle sacrifices some of its energy in order to "control" the following vehicles, some kinds of rewards may need to be introduced to incentivise the energy-efficient behaviour, for example, providing them vouchers for cinema, social events and restaurant visits (Schall and Mohnen, 2017).

If we consider the movement after 40 s, we can see that when the AV cooperates with the following vehicles, the following vehicles consume more fuel after 40 s until all of them have passed the stop line, than the scenario without cooperation. This is mainly because of the higher acceleration calculated by the OVM after 40 s. With more vehicles joining the platoon, the saving of fuel during 0 s and 40 s is not sufficient to offset the increase of fuel consumption after 40 s. Actually, in a multi-intersection environment, the movement after 40 s will be optimised in the next intersection. This can be seen by simply assuming that the stop line of the upstream intersection is located at 0 m and the green light starts at 0 s. The presented results apply only to one case with the specified simulation setting. More general simulations with various travel times are needed. Furthermore, when more vehicles are considered in the platoon, the speed oscillations of the following vehicles are suppressed significantly. This will contribute to better driving comfort for the following vehicles. Even though some following vehicles are not considered in the platoon, their behaviour is also influenced by the preceding vehicle, and their fuel consumption is reduced significantly. For example, the fuel consumption of the 4th vehicle in scenario R3 is 10.0% less than that in scenario R1 with $M_1$. This was also found by Treiber and Kesting (2014) and Wan et al. (2016).

Table 4: Fuel consumption of different scenarios in case 1

| Scenario | 1st vehicle | 2nd vehicle | 3rd vehicle | 4th vehicle | Total (mL) |
|---|---|---|---|---|---|
| scenario R1 | **48.1 / 48.1** | 53.1 / 57.3 | 55.0 / 62.9 | 56.2 / 67.2 | 212.4 / 235.5 |
| scenario R2 | **48.8 / 48.8** | 50.5 / 56.4 | 52.1 / 61.3 | 53.4 / 65.2 | 204.8 / 231.7 |
| scenario R3 | **50.7 / 50.7** | 49.3 / 56.9 | 49.2 / 60.9 | 50.6 / 64.4 | 199.8 / 232.9 |
| scenario R4 | **55.9 / 55.9** | 49.0 / 57.4 | 45.9 / 60.7 | 46.0 / 64.1 | 196.7 / 238.1 |

*4.2.2. Case 2: an AV is followed by mixed AVs and HVs*

When an AV is followed by mixed AVs and HVs, the question is whether the subsequent AVs need to activate the eco-driving function or just follow the preceding vehicle. In the simulations, the first vehicle is an AV in all scenarios. The second or third or fourth vehicle is another AV in scenario R6, R7, and R8, respectively. All other vehicles are HVs and their movements are according to the OVM. The last three vehicles in scenario R5 can either be automated or not, as their eco-driving functions are not activated and hence they behave the same as HVs.

- Scenario R5: There is only one platoon. The running cost is the sum of fuel consumption of four vehicles.
- Scenario R6: There are two platoons: the first vehicle and the last three vehicles. The running cost for the first platoon is the fuel consumption of the first vehicle, while the running cost for the second platoon is the sum of the fuel consumption of the last three vehicles.
- Scenario R7: There are two platoons: the first two vehicles and the last two vehicles. The running cost for the first platoon is the sum of the fuel consumption of the first two vehicles. The running cost for the second platoon is the sum of the fuel consumption of the last two vehicles.
- Scenario R8: There are two platoons: the first three vehicles and the last vehicle. The running cost for the first platoon is the sum of the fuel consumption of the first three vehicles. The running cost for the second platoon is the sum of the fuel consumption of the last vehicle.

The fuel consumption for every scenario in the simulations is shown in Table 5, and the state trajectories are shown in Figure 9. Comparing scenarios R6, R7, R8 to scenario R5, we observe that the activation of the eco-driving function in the following vehicles helps to reduce the total fuel consumption with both $M_1$ and $M_2$. This is mainly due to the reduction of their own fuel consumption, which is ranging from 15.4% to 24.6% with $M_1$ and from 13.1% to 18.9% with $M_2$. It also helps reduce the fuel consumption of the first AV due to fewer vehicles in its platoon as discussed previously. Eventually, with another AV, the reduction of fuel consumption ranges from 3.3% to 7.4% with $M_1$ and from 7.2% to 9.4% with $M_2$. This is different from the result of Stebbins et al. (2017) where giving speed advice to the following vehicles rarely makes a difference. This difference is mainly because in their approach only the leading vehicle can achieve the target position and speed. However, in the proposed method, the following AVs can also achieve the desired state, which can reduce the fuel consumption and travel time of the whole traffic. In Figure 9, the trajectories of the following AVs by the MPC show an obvious fallback behaviour and keep a larger gap than that in the OVM. In the OVM, the vehicle attempts to accelerate as soon as possible to achieve the optimal speed. In contrast, in the MPC method, the vehicle acts more rationally by considering the information of signal timing and state of the preceding vehicles. So, it reduces even further the fuel consumption to provide speed advice to the following AVs in the mixed AVs and HVs environment.

#### *4.2.3. Case 3: an AV is followed by other AVs*

When an AV is followed by other AVs, the question is whether the leading AV needs to consider the movements of the following AVs. If it does, what kind of benefits arise from this cooperation? In the simulations, all the vehicles are AVs and arrive at the stop line with maximum speed and zero acceleration with a fixed time headway 2s.

Table 5: Fuel consumption of different scenarios in case 2

| Scenario | 1st vehicle | 2nd vehicle | 3rd vehicle | 4th vehicle | Total (mL) |
|---|---|---|---|---|---|
| scenario R5 | **55.9 / 55.9** | 49.0 / 57.4 | 45.9 / 60.7 | 46.0 / 64.1 | 196.7 / 238.1 |
| scenario R6 | **48.1 / 48.1** | **41.5 / 49.9** | 48.9 / 59.0 | 51.7 / 64.0 | 190.2 / 221.0 |
| scenario R7 | **48.8 / 48.8** | 50.5 / 56.4 | **37.5 / 51.4** | 45.4 / 59.0 | 182.1 / 215.6 |
| scenario R8 | **50.7 / 50.7** | 49.3 / 56.9 | 49.2 / 60.9 | **34.7 / 52.0** | 183.9 / 220.5 |

- Scenario R9: Each AV optimises its trajectory separately and minimises its own fuel consumption.

- Scenario R10: The four AVs act as two platoons. The running cost for the first platoon is the total fuel consumption of the first two vehicles and the running cost for the second platoon is the total fuel consumption of the last two vehicles.

- Scenario R11: The four AVs act as two platoons. The running cost for the first platoon is the total fuel consumption of the first three vehicles, and the running cost for the second platoon is the fuel consumption of the last vehicle.

- Scenario R12: The four AVs act as one platoon. They minimise the sum of their fuel consumption.

The fuel consumption of every scenario in the simulation is shown in Table 6 and the state trajectories are shown in Figure 10. In the four scenarios, the results change very slightly and fall within 2 % for every vehicle and 1 % for the total in most cases. Nevertheless, the resulting trajectories may differ slightly. This outcome suggests that the cooperation among AVs does not make any obvious difference in the fuel consumption and the travel time. This conclusion is only valid for the current simulation setting and more simulation scenarios with different travel time and speed are needed, which will be shown in the following section.

Table 6: Fuel consumption of different scenarios in case 3

| Scenario | 1st vehicle | 2nd vehicle | 3rd vehicle | 4th vehicle | Total (mL) |
|---|---|---|---|---|---|
| scenario R9 | **48.1 / 48.1** | **41.8 / 49.7** | **38.7 / 50.9** | **36.8 / 52.1** | 165.4 / 200.7 |
| scenario R10 | **48.6 / 48.6** | **42.5 / 49.6** | **38.9 / 51.0** | **36.6 / 52.4** | 166.6 / 201.6 |
| scenario R11 | **49.0 / 49.0** | **42.7 / 50.2** | **39.1 / 51.4** | **36.2 / 52.1** | 167.0 / 202.6 |
| scenario R12 | **48.6 / 48.6** | **42.1 / 49.7** | **38.8 / 51.0** | **36.5 / 52.5** | 165.9 / 201.8 |

### *4.3. Simulations with different penetrations of AVs*

In this part, a simulation investigation is presented to show the performance of the proposed method in different penetrations of AVs. Please note that the cooperation of vehicles in a platoon relies on the vehicles' state information sharing. This can be achieved in the connected vehicle environment. If the vehicles are not fully connected, we assume that the AV can still detect the state of the first direct following vehicle via its built-in detectors. So the platoon size is limited to 2 in that condition. Another scenario without cooperation is also included for comparison.

- Scenario P1: All AVs consider their own fuel consumption only. It can also be seen as setting the maximum platoon size to be 1;
- Scenario P2: All AVs consider the fuel consumption of themselves and the first directly following vehicle. This can also be seen as setting the maximum platoon size to be 2;
- Scenario P5: All AVs consider the fuel consumption of themselves and all the following vehicles within the limit of maximum platoon size. The maximum platoon size is set to be 5.

When determining the maximum platoon size, we should trade off the calculation burden and communication reliability in practice. Large platoon size also implies that the AVs need to sacrifice more and have a higher probability to stop in order to "control" the vehicles far away. The stopping behaviour will also be discussed later.

The simulation of every scenario in every penetration rate lasts for 600s and is repeated twice. In all simulations, the cycle time is 60 s with green time 30 s and red time 30 s. Traffic demand is 850 veh/h. The type of vehicle is determined by comparing the penetration rate $p$ and a new generated random number between 0 and 1 when it enters the road. The time headway follows a truncated exponential distribution to ensure that no time-headway is less than 2s. The initial speed follows a normal distribution $N(10, 1)$ bounded by the speed limits and ensures that no collision happens at the entrance of the road (Ubiergo and Jin, 2016).

The average fuel consumption and travel time produced by the simulations are shown in Table 7 and Figure 11. Overall, both fuel consumption and travel time decrease with the increasing penetration of AVs under all scenarios. In any penetration studied, the scenario with cooperation outperforms or at least equals the scenario without cooperation. In general, as more vehicles join the cooperation, more benefits are gained in terms of fuel consumption and travel time. The benefits of cooperation are most evident for lower penetration rates, and a platoon size of 5 (P5) can reduce the fuel consumption by 22% with only a 60% penetration rate, which is better than the scenario of P1 with 100% penetration. However, as more AVs are brought into the system, the additional benefit from cooperation then decreases as there is not much room for further improvement. This is in line with the previous results from case 3 in section 4.2.3, where the benefit of cooperation for all four AVs was minor.

The travel time benefits are less significant than fuel consumption benefits and are not really present with 20% and 100% penetration of AVs. They then increase in a similar pattern to the fuel consumption and the effects of cooperation are similar. The reduction of travel time is mainly caused by the reduction of start-up lost time and queue discharge time as more vehicles pass on the green light and fewer vehicles stop on the red light thanks to the cooperation. However, when the penetration is 20%, the AVs are frequently interrupted by the preceding HVs, but when the penetration becomes 100%, there is no more room to reduce the travel time. Figure 11 shows that with the increasing penetration of AVs, the number of outliers in the fuel consumption is greatly reduced. Scenarios P2 and P5 also have much fewer outliers than scenario P1. This demonstrates that the cooperation can stabilise the traffic flow. This is also shown in Figure 12. No outliers are detected in the travel time. When the initial state is fixed, the travel time can only imply the terminal state, but all the intermediate states affect the fuel consumption. That is why the fuel consumption can show more information about the vehicles' movements.

The trajectories of vehicles with 20%, 60% and 100% penetration of AVs in three scenarios are shown in Figure 12. We can see that only optimising AVs themselves is not enough to achieve a system optimum. Sometimes the selfish behaviour of an AV can even worsen the traffic. This is especially serious when the penetration is low. When the leading AV attempts to slow down to save fuel, it causes a shock-wave along the link, which triggers some following HVs to stop. Even when the penetration of the AVs becomes 100%, sometimes this kind of selfish deceleration can still occur. In the cooperation scenarios (i.e., P2 and P5), the vehicles' trajectories are largely smoothed. The negative impact of eco-driving by the AVs on the following vehicles is also reduced. This is mainly because the fuel consumption of the following vehicles is directly included in the objective function of the AVs. The leading vehicles in each platoon also help the following vehicles to reach a high speed when crossing the stop line and avoid idling on the red light.

We also notice that the AV may stop in the middle of the road segment even in the cooperative scenarios with low probability. There are two main reasons, (1) the planned travel time is too long and (2) the following vehicles in the same platoon are widely dispersed. But please note that the stopping behaviour of the AV in cooperation scenarios does not harm the system. It does not increase the travel time or fuel consumption for the platoon. The AV never stops close to the stop line and does not block the following vehicles from passing the stop line. If stopping behaviour is not acceptable, one may add a larger minimum speed limit constraint on the AVs (Yang et al., 2017), but this may lead to infeasible result when the planned travel time is larger than the maximum travel time by applying the minimum speed limit. Then the speed advisory system will fail and the AV has to stop around the stop line. It results in higher fuel consumption and travel time for all the following vehicles. Thus, we choose not to include the larger minimum speed limit and allow the seldom stop behaviour.

## 5. Conclusions

Providing signal information to the vehicles on signalised urban roads is demonstrated to be an effective way to reduce the idle time and the fuel consumption. However, many eco-driving strategies have a negative impact on the efficiency of the intersection, and even cause a shock-wave in the middle of the road section. In this paper, a distributed and cooperative eco-driving method has been proposed for platoons to address these issues. The proposed eco-driving method has been designed for mixed traffic flow on an urban road, which consists of HVs and various penetrations of AVs. AVs attempt to pass the intersection on the earliest possible green time with a maximum desired speed and zero acceleration. All these settings are to maximise the traffic efficiency. In the paper, the jerk has been set as the control variable in order to increase the driving comfort. In the proposed control method, the fuel consumption of AVs and some following HVs is minimised over the horizon to achieve the eco-driving benefit to more vehicles. This cooperation largely smooths out the trajectory and suppresses any shock-wave. Then a platoon formation method has been proposed to apply the distributed and cooperative eco-driving strategy to achieve a better performance for the overall traffic. Three typical cases in mixed traffic have been studied with different platoon settings. Moreover, different penetrations of AVs have been studied in the simulation to show that the proposed method can adapt to various mixed traffic conditions.

Table 7: Simulation results and differences in various penetrations of AVs

| Penetration | Scenario | Fuel consumption | | Travel time | |
|---|---|---|---|---|---|
| | | Mean (mL) | Diff | Mean (s) | Diff |
| 0.2 | P1 | 55.3 | - | 37.4 | - |
| | P2 | 52.7 | -4.7% | 37.5 | 0.2% |
| | P5 | 48.4 | -12.6% | 37.3 | -0.3% |
| 0.4 | P1 | 50.0 | -9.6% | 34.1 | -8.7% |
| | P2 | 47.9 | -13.5% | 32.6 | -12.8% |
| | P5 | 46.6 | -15.9% | 31.7 | -15.2% |
| 0.6 | P1 | 47.6 | -13.9% | 34.1 | -8.8% |
| | P2 | 45.6 | -17.6% | 33.0 | -11.8% |
| | P5 | 43.1 | -22.1% | 31.6 | -15.5% |
| 0.8 | P1 | 46.1 | -16.8% | 33.1 | -11.6% |
| | P2 | 44.7 | -19.2% | 31.1 | -16.8% |
| | P5 | 43.2 | -21.9% | 31.2 | -16.5% |
| 1 | P1 | 43.5 | -21.3% | 31.1 | -16.8% |
| | P2 | 43.6 | -21.1% | 31.2 | -16.5% |
| | P5 | 42.5 | -23.2% | 31.2 | -16.5% |

From the analysis above, we can draw the following conclusions:

1. AVs can reduce their own fuel consumption and travel times when approaching a signalised intersection if the signal timing information is given.
2. When the penetration level is from low to moderate, the cooperation between AVs and HVs is seen to be beneficial in both fuel consumption and travel time.
3. However, this system level of cooperation requires a sacrifice from the lead AV which may be controversial to accept.
4. The level of sacrifice increases with the platoon size. As vehicles are added to the platoon of one AV then the leading vehicle has to overcompensate to affect the third and subsequent vehicle trajectories.
5. Even when the HVs are not included in the platoon, they still benefit from the preceding AVs.
6. It reduces the fuel consumption even further to provide speed advice to the following AVs in the mixed AVs and HVs compared with only controlling the leading vehicle on a green phase.
7. Larger platoon size helps to achieve a stronger reduction in fuel consumption and stabilise traffic flow.
8. The benefits of cooperation mean that the system can reach the same levels of benefit with 60% penetration rate as for 100% penetration without cooperation, which has implications for the transition towards a full penetration.
9. As the penetration rate reaches 100%, then the performance improvement resulting from cooperation is trivial and the sacrifice problem disappears.

These last two points taken together suggest that implementation the driving cooperation should vary over the implementation phase and that some higher levels of cooperation whilst desirable should be regulated or compensated with a promise to remove this obligation as the penetration rates increase.

In this paper, we assume that the future signal timing information is available to the AVs. This is fine for fixed timing control and adaptive signal control strategies that update signals every cycle (e.g. TUC (Diakaki et al., 2002, 2003)), but may not be true for other adaptive signal control systems, like SCOOT, where there is only very limited time for the AVs to response and may reduce the performance of the proposed method. There are two solutions: (1) Use the previous signal timing as the estimation when it is not available. When the signal timing is available at some time steps ahead, it may use the current instead. As the change between two cycles is unlikely to be too strong, e.g. it is limited to +/- 4 seconds in SCOOT, the performance impact may be suppressed, but would not vanish. (2) Develop a new algorithm within the SCOOT and SCATS to consider the AVs. In the current adaptive control schemes, the information is still mainly obtained from detectors like loop detectors. The information from AVs or CVs is not considered. So we think it is an interesting topic to develop new intersection control algorithms to take the advantage of new information from AVs and CVs. This is also our ongoing research work.

In the current work, the signal timing is assumed to be given. In the next step, it will achieve a better performance gain to optimise the signal timing and trajectory simultaneously either for the local intersection or traffic network.

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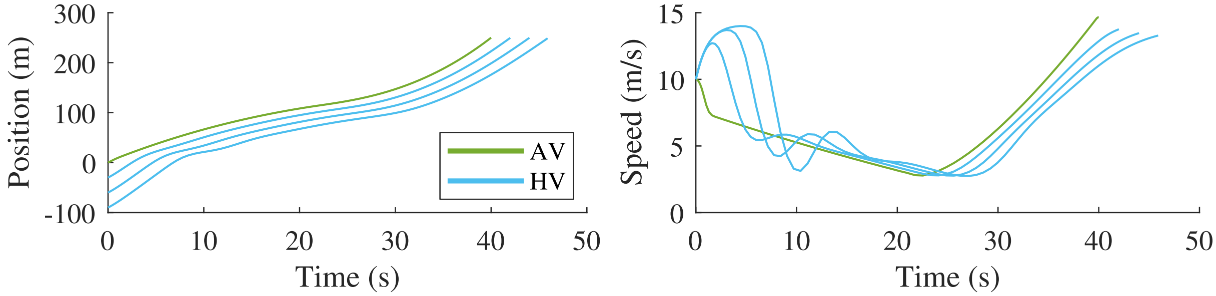
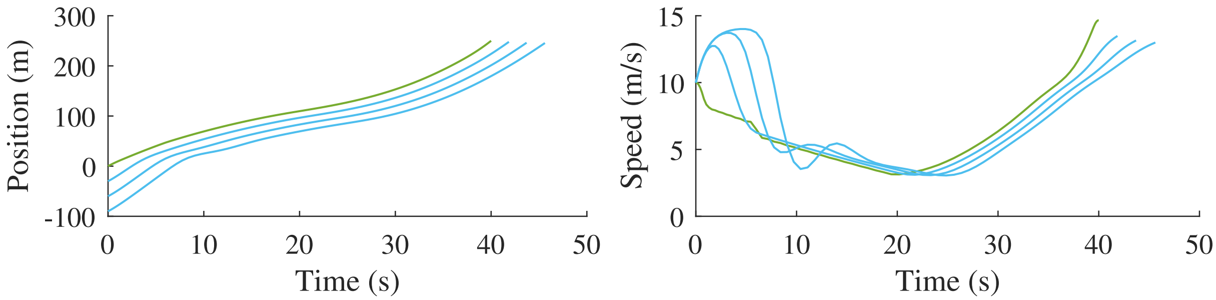
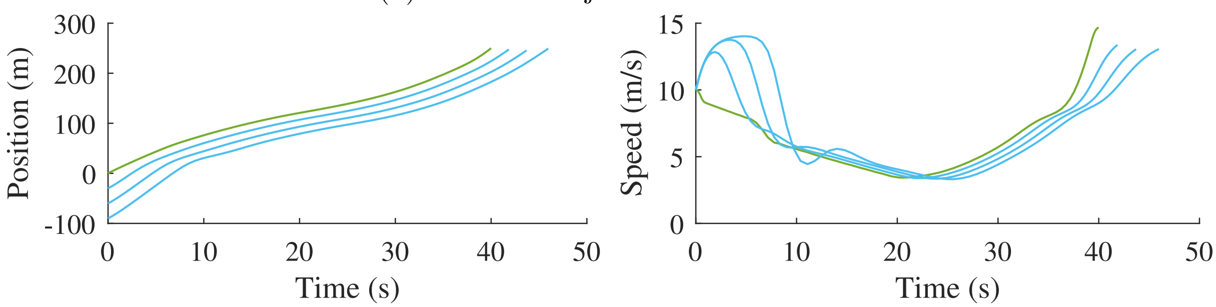


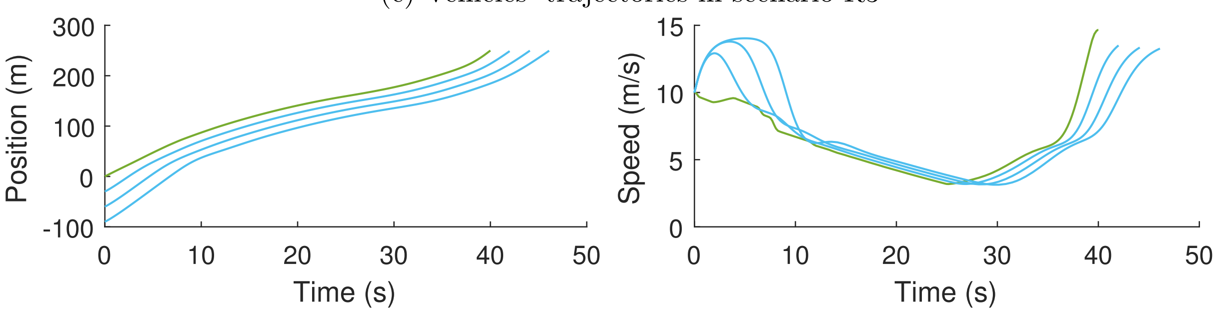

(a) Vehicles' trajectories in scenario R1




(b) Vehicles' trajectories in scenario R2

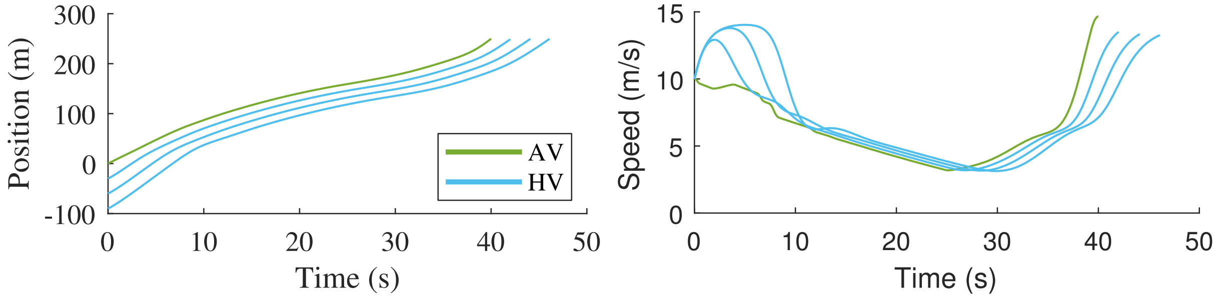



(c) Vehicles' trajectories in scenario R3

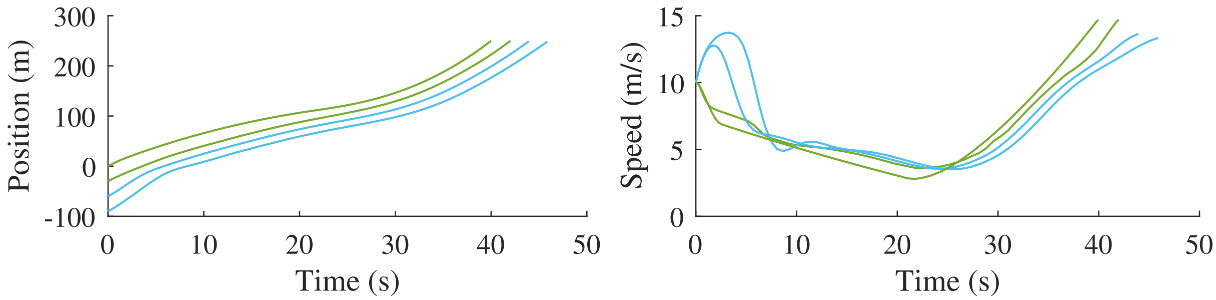



(d) Vehicles' trajectories in scenario R4

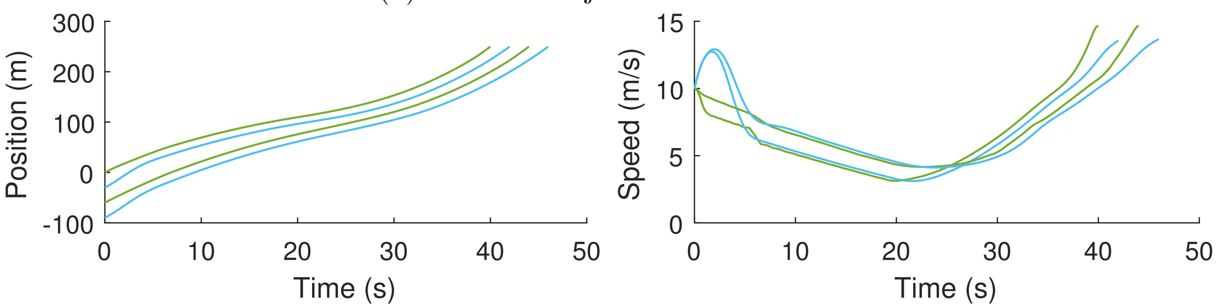
Figure 8: State trajectories of all vehicles under four scenarios in case 1



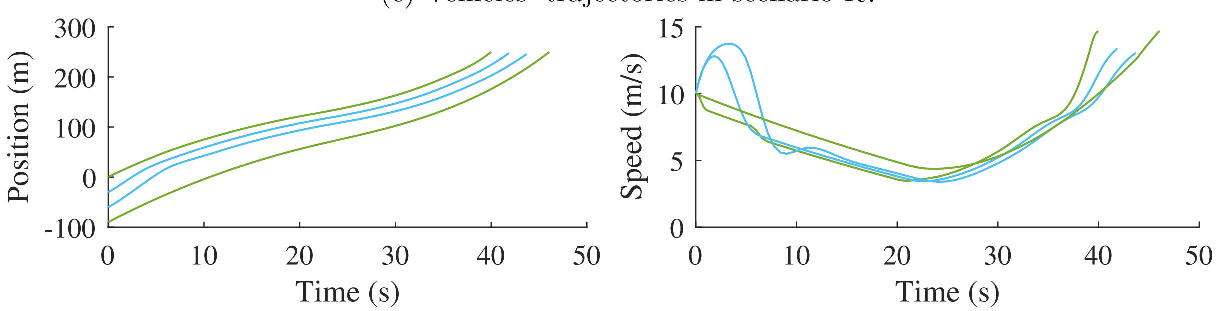

(a) Vehicles' trajectories in scenario R5




(b) Vehicles' trajectories in scenario R6

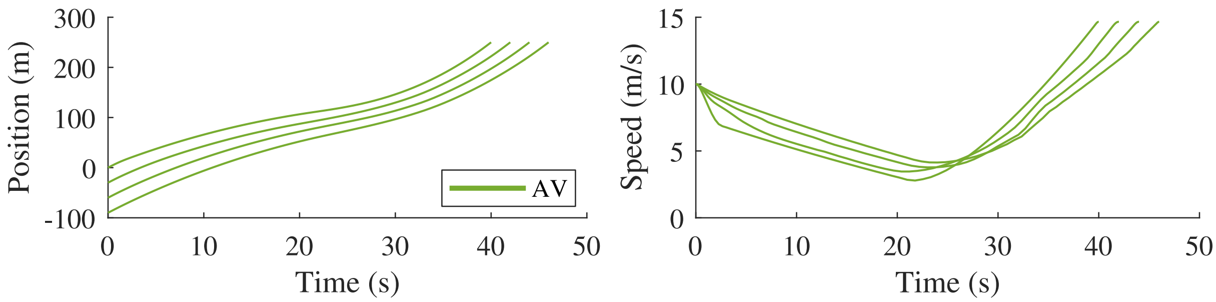



(c) Vehicles' trajectories in scenario R7

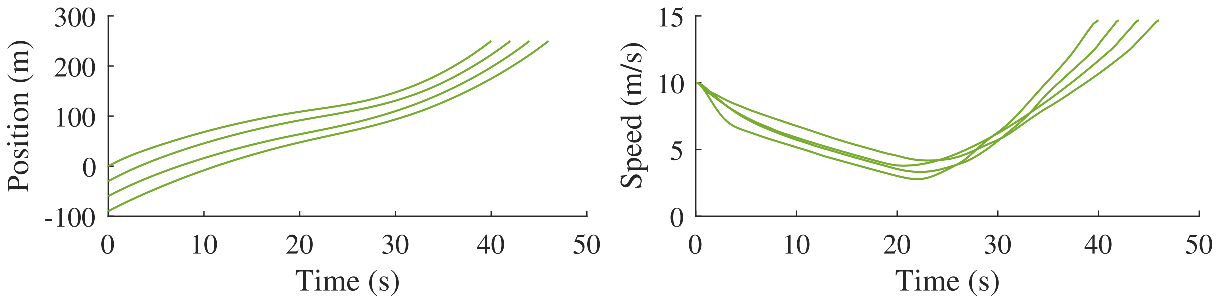



(d) Vehicles' trajectories in scenario R8

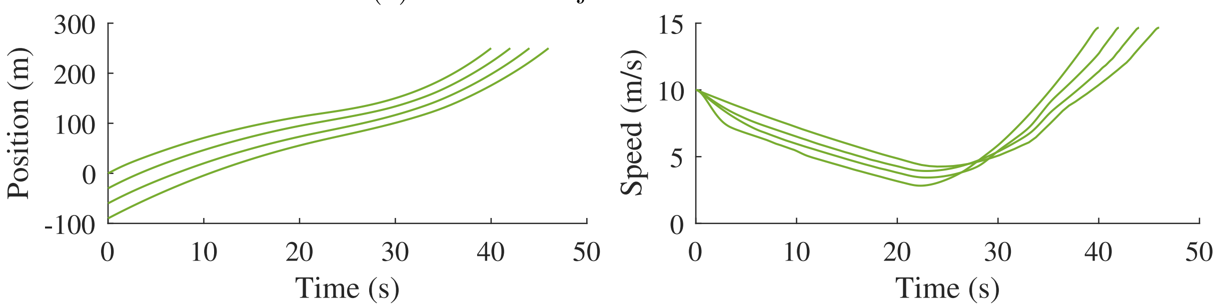
Figure 9: State trajectories of all vehicles under four scenarios in case 2



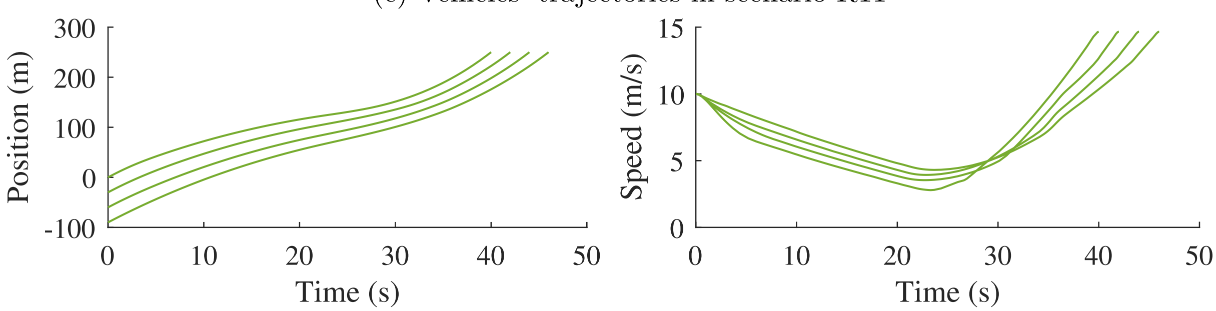

(a) Vehicles' trajectories in scenario R9




(b) Vehicles' trajectories in scenario R10

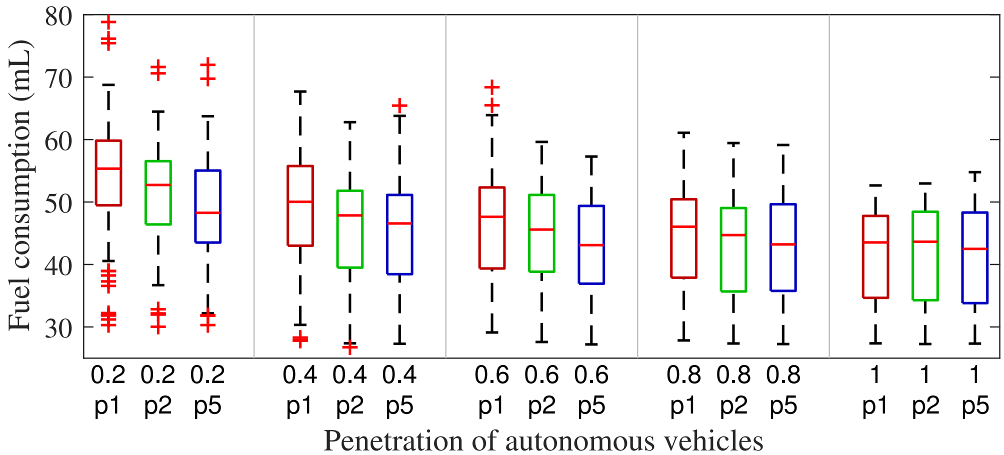



(c) Vehicles' trajectories in scenario R11

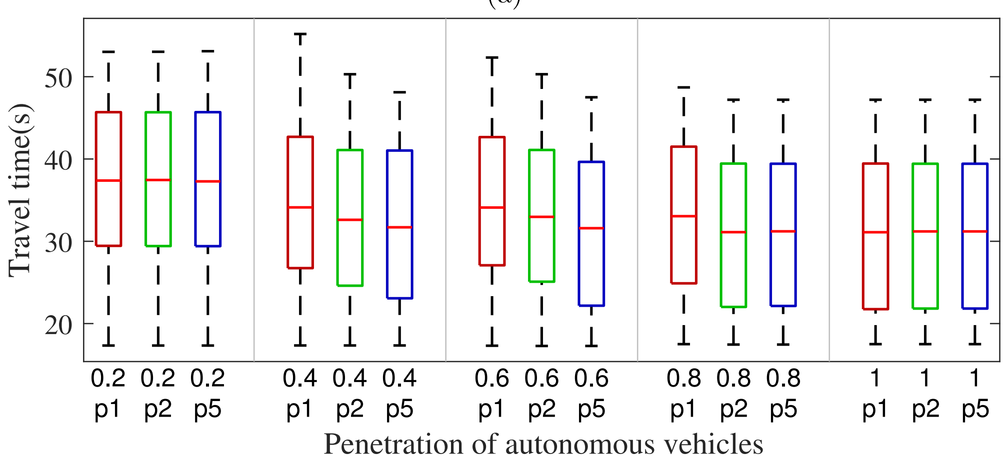



(d) Vehicles' trajectories in scenario R12

Figure 10: State trajectories of all vehicles under four scenarios in case 3

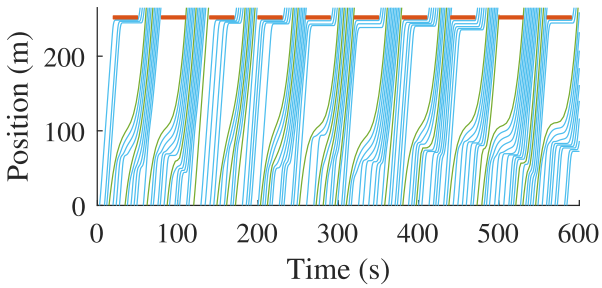



(a)

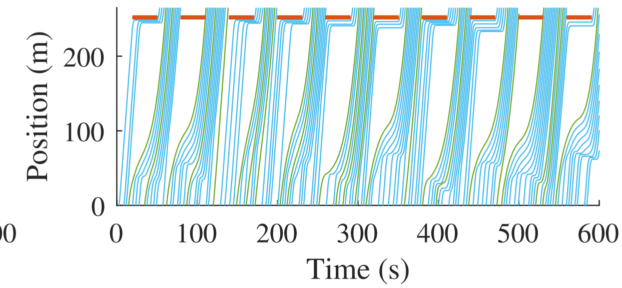



(b)

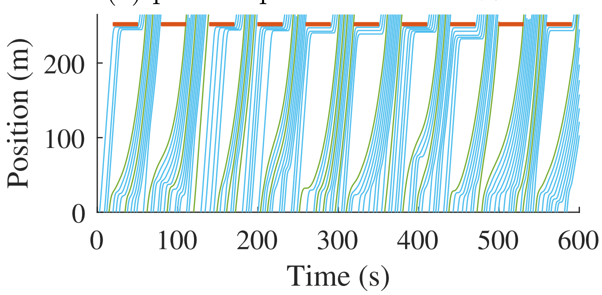
Figure 11: Simulation results in different penetrations of AVs. (a) fuel consumption, (b) travel time



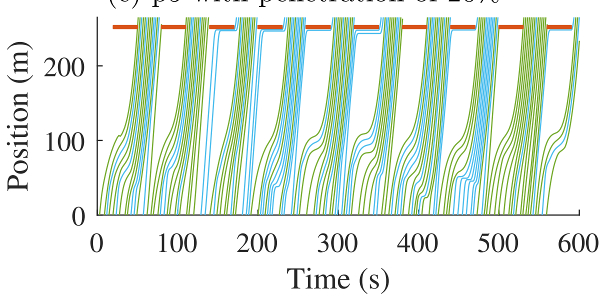

(a) p1 with penetration of 20%



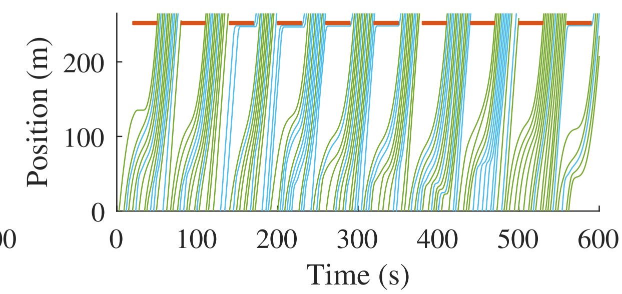

(b) p2 with penetration of 20%



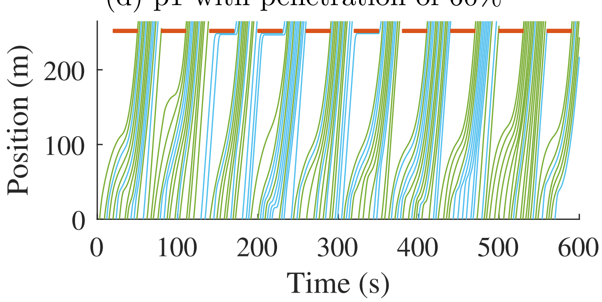

(c) p5 with penetration of 20%



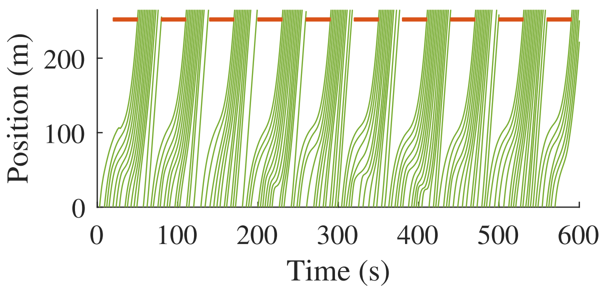

(d) p1 with penetration of 60%



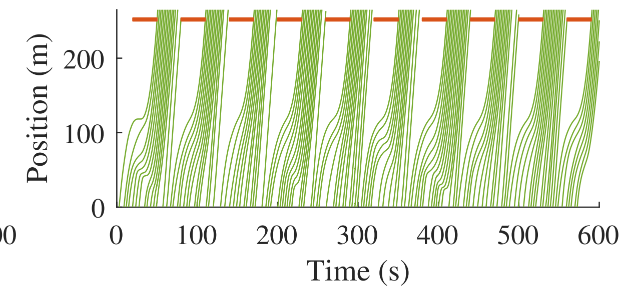

(e) p2 with penetration of 60%



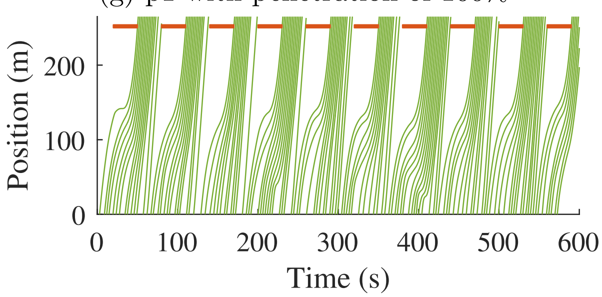

(f) p5 with penetration of 60%




(g) p1 with penetration of 100%




(h) p2 with penetration of 100%




(i) p5 with penetration of 100%

Figure 12: Some examples of trajectories in different penetrations of AVs