Eco-Driving of General Mixed Platoons with CAVs and HDVs

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***Abstract*—Eco-driving has been widely investigated over the last decade, but most studies focused on an individual vehicle or a vehicle platoon consisting of pure connected and automated vehicles (CAVs). Recently, mixed vehicle platoons consisting of both CAVs and human-driven vehicles (HDVs) have attracted much interest, considering the fact that HDVs will mix with CAVs in the traffic system for a long period. This paper proposes an eco-driving strategy for mixed platoons, composing of both offline planning and online tracking. In offline planning, an energy-efficient speed reference and a gearshift reference are determined by using the characteristics of each vehicle and future traffic information through dynamic programming. Offline planning optimised the vehicle speed and gearshift to allow the vehicle powertrain working at a high efficiency region. In online tracking, two different types of model predictive controls (MPCs) are proposed to control the CAVs in real-time. The MPCs are designed to achieve precise speed reference tracking performance and guarantee platoon string stability, respectively. Meanwhile, HDVs within the mixed platoon can be located anywhere in the platoon except working as the first vehicle to improve flexibility. Therefore, the proposed eco-driving strategy is applicable to mixed platoons with more general structures in ordering. The key contribution of this study is that the proposed eco-driving strategy can optimise the total fuel consumption for general mixed platoons. Simulation results show that the proposed eco-driving strategy improves the fuel economy of a mixed platoon by up to 6.39% compared to the benchmark conventional-adaptive cruise control strategies.**

***Index Terms*—Eco-driving, speed optimisation, model predictive control, connected and automated vehicles, mixed platoon**

I. Introduction

Nowadays, the transportation sector consumes more than 60% of the fossil fuel energy globally and has led to a significant increase in air pollutant emissions [1]. Therefore, improving energy efficiency in transportation systems has become essential. The vehicle platoon organises vehicles on the same route into a cluster with a desired longitudinal velocity whilst maintaining safe inter-vehicle distances. The vehicle platoon has great potential in reducing fuel consumption of vehicles within the platoon [2]. The connected and automated vehicle (CAV) within a platoon can connect to other CAVs or infrastructures based on vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and vehicle-to-everything (V2X) communications, and intelligent transportation systems (ITS) [3], [4]. There is a consensus that CAVs will coexist with human-driven vehicles (HDVs) on the road for a long time. Hence, it is important to develop mixed platoons consisting of both CAVs and HDVs. The key challenges of mixed platoons are that the motion control of involved HDVs are not definitive [5] and the behaviours of HDVs are not programmable as CAVs. To address these challenges, many human driving models have been developed to characterise the HDV behaviours in the car-following platoon [6]. The optimal velocity model (OVM) has been widely adopted to develop model-based [7]–[9] and data-driven platooning control [10] for mixed platoons.

Eco-driving strategies can assist vehicles to operate in energy efficient conditions by running under optimised speed profiles. Hence, it is generally recognised that an eco-driving strategy can substantially improve the fuel economy of individual vehicles [11], [12]. Most eco-driving strategies have been developed for CAVs. By using communication techniques, the CAV can access more traffic information than conventional vehicles. An offline planning strategy allows eco-driving to create the most energy efficient reference speeds for the entire route based on vehicle characteristics, traffic and road conditions [13], [14]. Due to the dependence on predicted future route information, offline planning strategies have shown poor results against unexpected disturbances. To enhance the robustness, real-time eco-driving optimisation strategies have been developed to minimise the energy consumption of CAVs considering uncertainties from other traffic participants [15], [16]. This enables the CAV to achieve higher energy efficiency whilst maintaining safe inter-vehicular distances. However, the preview information about other traffic participants provided by V2X or learning-based predictive models is limited to a short horizon [15], [17]. Therefore, real-time optimisation strategies may be suboptimal and also increases the online computational burden because of using the sophisticated vehicle model. Eco-driving strategies using a two-stage hierarchical control to address the gap between offline planning and

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real-time optimisation have been investigated [18], [19]. In the offline planning stage before departure, the energy consumption of CAV is optimised using global optimisation based on the known vehicle characteristics and road conditions. In the online tracking stage after departure, the CAV is controlled to track the reference speed and adjust the CAV motions in responding to real-time traffic situations. These two-stage strategies combine the advantages in both offline planning and real-time optimisation. Meanwhile, several studies have examined the capability of eco-driving in improving the total energy efficiency for an entire pure CAV platoon [20], [21].

Ecological cooperative adaptive cruise control (eco-CACC) is a typical eco-driving strategy for a CAV platoon, which makes a cooperative adaptive cruise control (CACC) platoon more efficient through applying platoon-based eco-driving strategies. Eco-CACC optimises the energy consumption of the vehicles and ensures all vehicles within the platoon track the reference speed with safe inter-vehicle distances [2], [20], [22]. Additionally, a two-stage hierarchical control for eco-platoons has been designed in [23], [24]. The eco-CACC designs reviewed above are all based on platoons consisting of pure CAVs. However, the penetration rate of CAVs in the transportation system will remain at a relatively low level for a long time, resulting in a mixed traffic environment. Therefore, we have to study platoons composed of both CAVs and HDVs on the future road.

Eco-driving strategies for the mixed platoon can be divided into two categories. The first category is to reduce the impact of the HDVs in the platoon, meanwhile the CAV fuel consumption is optimised based on the prediction of the HDV's speed trajectory [25]. However, the fuel consumption of HDVs is not considered in the optimisation. In the second category, the mixed platoon is led by a CAV and all the CAVs must be located in front of the HDVs within each platoon [26]. This strategy considers the fuel consumption of both CAVs and HDVs within the platoon. However, this strategy is only applicable to platoons with fixed structures. Since all HDVs in the fixed-structure platoon must follow CAVs, the platoon may be very short and unable to offer the benefit of platooning under extreme conditions.

Therefore, this study aims to design an eco-driving strategy to improve the total energy consumption of a mixed platoon in general structures. The control of the mixed platoon can be realised by controlling CAVs to influence the speed of HDVs [27], [28]. In these studies, the car-following model is utilised to describe the dynamics of HDVs within the platoon. The proposed eco-driving strategy contains two stages: offline planning and online tracking. In offline planning, the global optimisation strategy minimises the fuel consumption for the mixed platoon. In online control, the hybrid distributed model predictive controller (MPC), consisting of a speed tracking MPC and a min-max MPC, tracks the reference speed and maintains the platoon string stability. This is because guaranteeing string stability is essential to the success of vehicle platoon. The entire mixed platoon satisfies the head-to-tail string stability [29] and min-max MPC control for each CAV considers the ℓ_2 string stability [30]. A detailed string stability analysis is referred to our previous works [10], [30], [31]. The contributions of this work are summarised as follows:

Fig. 1. The mixed platoon controlled by the proposed eco-driving strategy.

- A two-stage eco-driving strategy is developed to optimise and control the entire mixed platoon. In literature, the HDVs are placed in specific locations. In comparison, the proposed strategy is applicable to a more general mixed platoon structure.
- The offline planning minimises both the energy consumption of the platoon and the impact on other traffic participants. Offline planning is developed based on solving a multi-objective global optimisation problem. The first objective is to reduce the total energy consumption of the platoon. The second objective is to minimise speed deviations from the average traffic speed and therefore to prevent vehicle selfish optimisation. Moreover, a reference speed close to the average speed can reduce the difficulty in speed tracking.
- A hybrid distributed MPC is used to control CAVs at different locations within the mixed platoon. The proposed MPC is robust against disturbances from the predecessors and guarantees the mixed platoon string stability. The MPC also leverages the prediction of HDVs in the mixed platoon to improve the speed tracking performance.

The remainder of this paper is structured as follows. The eco-driving strategy for mixed platoon is outlined in Section II. The CAV dynamics, car-following model, vehicle fuel model and energy consumption model are given in Section III. The offline planning and online tracking designs are presented in Section IV and Section V, respectively. Simulation results are provided and analysed in Section VI, followed by the conclusions in Section VII.

II. Description of the Two-Stage Eco-Driving Platoon

The aim of the proposed eco-driving strategy is to improve the fuel economy of the entire mixed platoon. Meanwhile, reducing the impact on other traffic participants is required to avoid influencing the traffic efficiency. An example of the six-vehicle mixed platoon is shown in Fig. 1. All vehicles with the blue signal symbols are CAVs, and two vehicles are located between the CAVs are HDVs within the platoon. The red car in the front location represents the first vehicle in the platoon. The

CAVs in the platoon are assumed to be capable of receiving traffic information and other vehicle information from V2X. It is assumed that the HDVs in the platoon cannot receive any information from communication systems. However, the HDVs can access V2V broadcast communications [32]. These can transmit some basic vehicle characteristics to adjacent CAVs. The HDVs located between two CAVs in the mixed platoon are represented by HDV sub-platoons. Each HDV sub-platoon may contain one or more HDVs. In addition, there may be more than one HDV sub-platoons within a mixed platoon. In this paper, all the vehicles within the platoon are indexed by $i \in \{0, 1, ..., n\}$. Meanwhile, the head and rear HDVs in the HDV sub-platoons can also be named by h and H, respectively.

The architecture of the two-stage eco-driving strategy for mixed platoon is shown in Fig. 2. The proposed strategy uses the unidirectional predecessor-following (PF) topology in online tracking with only the current acceleration of the preceding vehicle being shared. The platoon is created based on vehicle models and controlled by hybrid distributed MPC in real-time.

The offline planning can produce a fuel-efficient reference speed for the entire mixed platoon before the trip starts. First, the data fusion will provide the average traffic speed, traffic density and other relevant information based on the route map, route plan and traffic data. Then, the reference speed is generated from a global optimisation model with multiple objectives. The reference speed is designed for energy optimisation upon vehicle characteristics and road conditions. Meanwhile, the distance-based point-mass model is chosen in offline planning to create the reference speed. In a distance-based reference speed, any reference tracking error from the adaptation of the vehicle speed only influences the nearby positions, while the reference speed remains unaffected in other positions [33]. The design details of the offline planning are provided in Section IV.

The online tracking is designed to track the reference speed and to maintain the platoon stability in real-time. The vehicle location identification is used to ascertain the order of the platoon. The leading vehicle decision enables the first CAV to track the reference speed or to follow the vehicle ahead of the platoon based on real-time traffic information. The vehicle ahead of the platoon is represented by *Pre* in the rest of the paper. The *Pre* is represented by the yellow taxi in front of the first red CAV in Fig. 1. Speed tracking MPC and min-max MPC are applied to different CAVs according to the vehicle location. The min-max MPC focuses on diminishing inter-vehicle distance and speed tracking errors. The speed tracking error produced by HDVs within the mixed platoon may accumulate in all subsequent vehicles. Therefore, the speed tracking MPC is designed to reduce the impact from HDVs. The speed tracking MPC uses the predicted motion of HDVs within the mixed platoon to introduce a flexible inter-vehicle distance. Meanwhile, the gear shift control provides the gear positions of the CAVs when the platoon cannot follow the reference speed. The gear shift control can provide an optimal gear position based on a function of acceleration in the velocity and acceleration map [34]. An optimal gear map

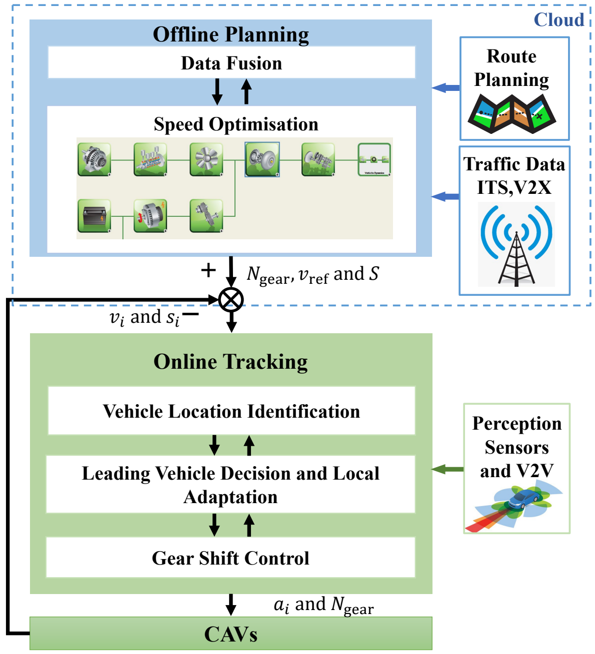

Fig. 2. The architecture of the proposed eco-driving strategy.

is created for each CAV based on a three-dimensional data set. The data set includes three-dimensional engine fuel maps with fuel mass flow rate, acceleration and speed data for each gear. The design details of the online tracking are provided in Section V.

III. Modelling of the Mixed Platoon

In offline planning, all vehicles within the platoon are assumed to have the same reference speed, and the order of vehicles in the platoon is kept. The distance-based point-mass model is chosen in this stage. In online tracking, the motions of CAVs are described by the time-based point-mass model, and Newell's car-following model (NCM) has been used to describe the HDVs motions.

A. CAV Dynamics Modelling

In this paper, the mixed platoon does not change lanes, so the model only focuses on longitudinal dynamics. The vehicle dynamics are modelled in two different ways. A distance-based point-mass model is employed in offline planning, and a time-based point-mass model is used to design the online tracking. They are all based on the point-mass model since the model can be applied to any vehicle. This makes it a viable alternative for use in either a homogeneous platoon or a heterogeneous platoon. In offline planning, each vehicle within the mixed platoon assumes to be travelling at the same speed so that a speed reference can be implemented to the whole CAV platoon in offline planning. In the distance-based point-mass model, the longitudinal distance step Δs is assumed to be constant. The discrete-time distance-based vehicle dynamics can be described by:

$$
\begin{aligned}
v(k+1) &= v(k) + \frac{a(k)\cdot\Delta s}{v(k)} \\
t_d(k+1) &= t_d(k) + \frac{2\cdot\Delta s}{v(k) + \frac{a(k)\cdot\Delta s}{v(k)}}
\end{aligned}
\tag{1}
$$

where $k \in \{0, 1, ..., N-1\}$. $t_d(k)$ is the travel time in the distance-based model. The CAV acceleration is generated by the engine torque or brake torque.

In this study, the mixed platoon follows the PF topology. Therefore, the CAV within the platoon controls the speed based on preceding vehicle information in real-time. In real-time control, the vehicle must be ensured to satisfy the distance-dependent safety constraints. Thus, the time-based point-mass model for online tracking is described as:

$$
\begin{aligned}
x(t+1) &= x(t) + T_s \cdot v(t) \\
v(t+1) &= v(t) + T_s \cdot a(t)
\end{aligned}
\tag{2}
$$

where $x(t)$ and T_s represent the vehicle position and time interval, respectively. This time-based point-mass model is applied for CAVs with speed tracking MPC. The CAV equipped with a min-max MPC focuses on the car following performance and stability. For leader-follower vehicle platooning, the following vehicles maintain an inter-vehicle distance and follow the preceding vehicle's speed. Therefore, the time-based point-mass model (2) has been modified to be a platoon error system represented by:

$$
\begin{aligned}
\Delta p_i(t+1) &= \Delta p_i(t) + T_s \Delta v_i(t) \\
\Delta v_i(t+1) &= \Delta v_i(t) - T_s a_i(t) + T_s a_{i-1}(t)
\end{aligned}
\tag{3}
$$

where

$$
\Delta x_{i,e} = \begin{bmatrix} \Delta p_i \\ \Delta v_i \end{bmatrix}. \tag{4}
$$

$\Delta p_i(t)$ and $\Delta v_i(t)$ are the distance and speed tracking errors between vehicles $i-1$ and i, respectively. The distance error is the error between the actual and desired inter-vehicle distances.

B. HDV Car-Following Model

The HDVs in the mixed platoon cannot be controlled directly. For this reason, the car-following model can be utilised to describe the dynamics of the HDV. The intelligent driver model (IDM) [35], the full velocity difference (FVD) model [36] or the OVM can all be used to describe the dynamics of HDV in a platoon. All the above human driver models need to know the parameters of each specific driver and vehicle. However, NCM, which does not require the parameters of each specific driver and vehicle, has been extended to HDVs modelling in this study. The NCM is widely used to simulate vehicle trajectories [37]–[39]. The NCM has assumed that the movement of the following vehicle is consistent with the lead vehicle in a homogeneous space. The speed trajectory of the following vehicle is identical to the preceding vehicle with a

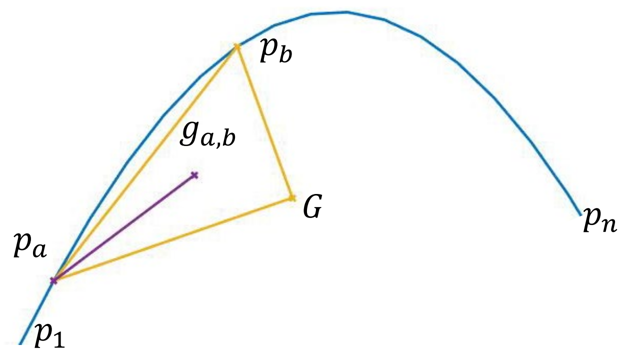

Fig. 3. An open shape contour (blue curve) with TCDs for point p_a.

time lag and space lag. The movement of the first and last HDVs in the HDV sub-platoons are described by:

$$x_h^h(t\cdot T_s + \delta t_h) = x_{h-1}^h(t) - d_h \tag{5}$$

$$v_h^h(t\cdot T_s + \delta t_h) = v_{h-1}^h(t) \tag{6}$$

$$x_H^h(t\cdot T_s + \sum_{h+1}^{H} \delta t_i) = x_h^h(t) - \sum_{h+1}^{H} d_i \tag{7}$$

$$v_H^h(t\cdot T_s + \sum_{h+1}^{H} \delta t_i) = v_h^h(t) \tag{8}$$

where $x_h^h(t)$ and $v_h^h(t)$ are the position and velocity of first HDV in the HDV sub-platoons, respectively. $x_H^h(t)$ and $v_H^h(t)$ are the position and velocity of the last HDV in the HDV sub-platoons, respectively. δt_i and d_i are the reaction time and the minimum stop distance of the HDV i, respectively. t is the discrete sample times. The motion of the following vehicle is affected by the front vehicle. Meanwhile, the CAV adjacent to the HDV can perceive and record the motion of the HDV. This data can be used to address time lag and space lag introduced from a curve matching algorithm.

C. Curve Matching Algorithm

The main idea of the curve matching algorithm is to iteratively move a speed trajectory by a motion vector until it coincides with another speed trajectory. Therefore, the motion vector is an accumulated time lag and space lag between vehicles. A Triangular Centroid Distances (TCDs) method has been adopted to pair two relative trajectories [40]. An example of TCDs for a point on the open contour is shown in Fig. 3. TCDs use the existing relationship between each point on the shape, with the central point describing the object's shape. The sequence of equidistant sample points p can be found on the open shape contour in Fig. 3, with starting point p_1 to the end point p_n. For the point p_a on the open contour, the other point $p_b (b = 1, 2, ..., n, a \neq b)$ can be found on the open contour. Therefore, a triangle $\Delta p_a G p_b$ with these two points and the centroid point G of this open contour can be created. $n-1$ triangles can be found for point p_a when the other point p_b is chosen as a different value. For each triangle, a centroid points $g_{a,b}$ can be found. The TCDs for point p_a is an $(n-1)\times 1$ matrix containing the distance between the points p_a and $g_{a,b}$ of each triangle. The TCDs for this open contour is an $(n-1)\times n$ matrix containing TCDs for each point on the open contour. The advantage of using TCDs in curve matching is twofold. First, TCDs have a tolerance for a substantial range of shape deformations. The NCM method assumes that the speed trajectories are identical to different vehicles, but actually are subject to deformations. Therefore, the TCDs shape descriptors has better accuracy in pinpointing relative trajectories compared with the conventional matching algorithms. Second, the TCDs can solve whole-to-part and part-to-part shape matching problems. Thus, the speed trajectories of shorter period HDVs are able to match the preceding vehicle's more extended speed trajectory. The paired trajectories are obtained by minimising the shape disparity between two trajectories based on the TCDs methods. The TCDs is applied to pair the speed trajectory H_H of the last HDV H in the HDV sub-platoons with the speed trajectory A_{h-1} of an adjacent CAV $h-1$ in front of the HDV sub-platoons. A_{h-1} is normally longer than H_H as CAVs have a more extensive speed trajectory in terms of knowledge history. Therefore, finding the matched trajectories is a whole-to-part partial shape matching problem. The set $A^s_{h-1}, s=\{1,...,S\}$ is created. Each speed trajectory in this set has the same size as H_H, and the initial point of A^1_{h-1} is the first feasible point until to initial point of A^S_{h-1} is the last feasible point in the CAV speed trajectory. The minimum shape dissimilarity can be calculated by:

$$\begin{aligned}\mathrm{Diss}(A^s_{h-1}, H_H) =& \min_{s\in\{1,...,S\}}|(TCD_s(A^s_{h-1})) \\ & -(TCD_s(H_H))|\end{aligned} \tag{9}$$

where TCD_s is the shape descriptor of speed trajectory. To facilitate the implementation, this paper adopts the (3) and (4) of [40] to create TCDs for each speed trajectory. Then, the motion vector for two trajectories matched can be calculated by:

$$\begin{aligned}\tau_H &= -\frac{1}{K}\sum_{k=1}^{k}(H_{H,k}-A_{h-1,k}) \\ &= (-\delta t_H, d_H)\end{aligned} \tag{10}$$

where $A_{h-1,k}$ and $H_{H,k}$ are the paired points from A^s_{h-1} and H_H; K is the total number of the paired points; τ_H is the motion vector of last HDV. The minimum motion vector can be applied to the NCM to predict the motion of HDVs in the platoon.

D. The Models for Fuel and Energy Consumption

In this paper, the HDVs have only limited capability of transferring data to other vehicles via V2V broadcast. The eco-driving strategy cannot access the engine fuel efficiency map in optimising the vehicle's fuel energy of HDVs. Meanwhile, the HDV gear shift cannot be controlled in the online tracking. Hence, the speed optimisation for HDVs with limited data is based on energy consumption minimisation without the fuel efficiency map and gear shift control. On the other hand, the CAVs have the higher transmission bandwidth and are thus able to provide sophisticated vehicle characteristics to the cloud for offline optimisation. The speed optimisation for CAVs is based on fuel consumption minimisation. Furthermore, this paper uses the realistic energy model for CAVs in speed optimisation and simulation. The engine fuel mass flow rate is described using the engine fuel efficiency map obtained from *Autonomie* [41] rather than the approximate fuel consumption model. In this paper, each CAV within the mixed platoon has its own specific engine fuel efficiency map. An example of an engine fuel efficiency map for CAV is illustrated in Fig. 4. The engine fuel mass flow rate can be described as

$$\dot{m}_f = f(T_\omega, \omega_e) \tag{11}$$

where the crankshaft rotational speed ω_e is described as:

$$\omega_e = r_{\mathrm{gb}}\omega_{\mathrm{wheel}} \tag{12}$$

where r_{gb} and ω_{wheel} are the ratio of each gear (including the final drive ratios) and wheel rotational speed, respectively. T_ω is the output torque of the internal combustion engine, which is related to wheel torque, gearbox efficiency and r_{gb}. The wheel-to-distance energy model is implemented on the HDV [26], [42]. The HDV longitudinal motion is governed by the Newton's second law of motion which is given by:

$$\begin{aligned}ma(k) &= F_w(k)-F_r(k)-F_{\mathrm{air}}(k) \\ &= F_w(k)-mg\left(\cos(\theta(k))C_{\mathrm{rr}}+\sin(\theta(k))\right) \\ &\quad -\frac{\rho A C_d}{2}v(k)^2\end{aligned} \tag{13}$$

where $F_w(k), F_r(k)$ and $F_{\mathrm{air}}(k)$ are the engine force or braking force applied at the wheels, resistance force and aerodynamic drag force, respectively; k is the sampling step; C_{rr} is the coefficient of rolling resistance; $\theta(k)$ is the road slope; ρ is the air density; A is the vehicle front area; m, $v(k)$ and $a(k)$ are the mass, velocity and acceleration of the vehicle, respectively. C_d is the aerodynamic drag coefficient.

For simplification, each vehicle has a constant aerodynamic drag coefficient C_d, and its aerodynamic drag force F_{air} only varies with vehicle speed. In practice, the distances of a vehicle to its predecessor and follower both affect the aerodynamic drag coefficient of the vehicle. The platoon with shorter inter-vehicle distance has less aerodynamic drag force at the same speed [43]. Some studies provided approximately methods to calculate the aerodynamic drag coefficient based on inter-vehicle distances [44]–[46].

The net energy needed at the wheels of the HDVs is calculated by:

$$\begin{aligned}E^h(k) &= \Delta s\Big(ma(k)+mg\Big(\cos(\theta(k))C_{\mathrm{rr}} \\ &\quad +\sin(\theta(k))\Big)+\frac{\rho A C_d}{2}v(k)^2\Big)\end{aligned} \tag{14}$$

where $E^h(k)$ is the net energy needed and Δs is the vehicle displacement.

IV. Offline Planning

Offline planning aggregates the traffic data and generates a reference speed to minimise fuel consumption and energy consumption within the most feasible speed range.

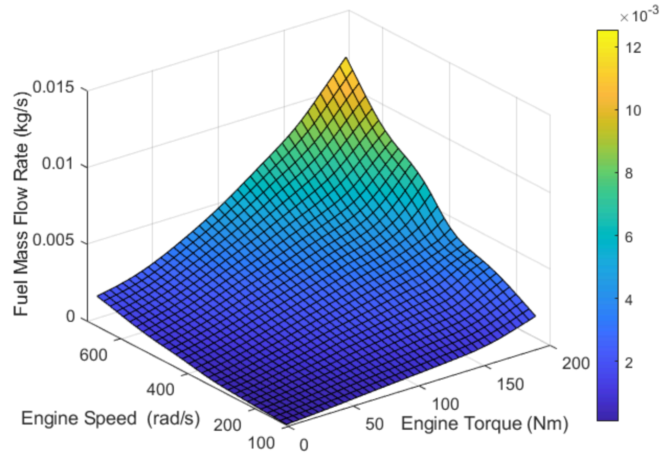

Fig. 4. Engine fuel map extracted from Autonomie.

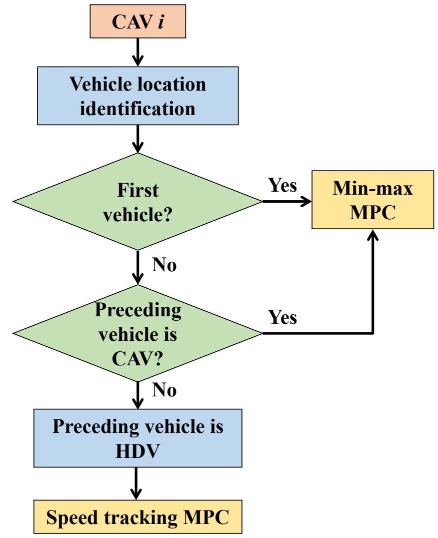

Fig. 5. Flowchart of the MPC assigned by vehicle location identification.

A. Data Fusion

The offline planning uses traffic state information of future road segments from the ITS. In this paper, the average speed for the road segments is delineated through the Caltrans Performance Measurement System (PeMS) [47]. The primary data sources for the PeMS are the vehicle detector stations (VDS), which can provide the traffic density, rate of flow and average speed of each traffic segment. Meanwhile, each road segment contains at least one VDS. In addition, the PeMS can receive traffic updates every 30 seconds and disseminate the information.

B. Speed Optimisation

The offline planning generates the reference speed for the mixed platoon using the distance-based point-mass model (1). Dynamic programming (DP) with multiple objectives is applied to the platoon optimisation effort. Each CAV can calculate the engine fuel mass flow rate by (11), and the energy demand for each HDV is calculated by (14). The cost function is chosen as:

$$\begin{aligned} J_{\text{opt}} \quad = \quad & w_{o,1} \sum_{i=0}^{n} \sum_{k=0}^{N-1} \dot{m}_{f,i}(k) + w_{o,2} \sum_{i=h}^{H} \sum_{k=0}^{N-1} E_i^h(k) \\ & + w_{o,3} \sum_{k=0}^{N-1} \| v^p(k) - V_{\text{avg}}^m(k) \| \end{aligned} \tag{15}$$

where the first term of the cost function represents the fuel consumption for the CAVs based on powertrain characteristics; the second term represents the energy consumption for the HDVs based on vehicle characteristics; the third term represents the deviation of the platoon speed and the average speed of the current road segment. $V_{\text{avg}}^m(k)$ is the average speed of road segment and $v^p(k)$ is the platoon speed. $w_{o,1}$, $w_{o,2}$ and $w_{o,3}$ indicate the weights of the fuel consumption, energy consumption and speed deviation, respectively. The physical constraints of the vehicle are

$$\begin{aligned} T_{\omega,i}^{\min} \leq & T_{\omega,i}(k) \leq T_{\omega,i}^{\max}, \forall k \in \{0, 1, ..., N\}, \\ & \forall i \in \{1, 2, ..., n\}, \forall i \notin \{h, h+1, ..., H\} \qquad (16) \\ a^{\min} \leq & a(k) \leq a^{\max}, \forall k \in \{0, 1, ..., N\} \end{aligned}$$

where constraints are applied to the CAV engine torque and mixed platoon acceleration, respectively. $T_{\omega,i}^{\min}$ and $T_{\omega,i}^{\max}$ represent the minimum and maximum allowable engine torque output of CAV i, respectively. $a_{\min}$ and $a_{\max}$ represent the maximum deceleration and acceleration of the vehicle platoon, respectively. These values are determined based on the vehicle with the lowest relevant performance specifications and passenger comfort in the platoon. The platoon speed has been set within an average velocity range. The lower boundary of the speed range can mitigate the effect of selfish optimisation and thus reduce the impact on other traffic participants. Meanwhile, ensure that the platoon does not stop to save energy. The upper boundary of the speed range can serve to improve the feasibility of the reference in real traffic environment. The speed constraints can be written as:

$$\begin{cases} V_{\text{avg}}^m - 5\,\text{m/s} \leq v(k) \leq V_{\text{avg}}^m + 5\,\text{m/s}, \\ \quad \text{if} \quad v_{\text{limit}} > V_{\text{avg}}^m + 5\,\text{m/s} \\ V_{\text{avg}}^m - 5\,\text{m/s} \leq v(k) \leq v_{\text{limit}}, \quad \text{otherwise} \end{cases} \tag{17}$$

where v_{limit} is speed limit. To summarise, the offline planning will create a reference speed v_{ref}.

V. Online Tracking

Online tracking regulates the mixed platoon in real-time to track the reference speed and maintain the stability. In addition, the online tracking controls the mixed platoon to adapt the speed considering other traffic participants. It is to guarantee safety in driving. The corresponding MPC controller for each CAV is decided by vehicle location identification. As discussed in Section II, the speed tracking MPC is applied to the first CAV that follows the HDV sub-platoons within the platoon and the min-max MPC is applied to the rest of CAVs. The flowchart of vehicle location identification has been illustrated in Fig. 5, and is introduced in this section with details of MPCs.

A. Leading Vehicle Decision

After the vehicle location has been identified, the leading vehicle decision is applied to the first CAV in the mixed platoon. The leading vehicle decision is used to determine whether the first CAV should follow the virtual phantom vehicle or the *Pre*. The phantom vehicle is designed to be a leading vehicle and to track the reference speed when there is no *Pre* in the desired safety range. The speed reference provided by offline planning is in the speed and distance domain. Hence, the platoon tracks the reference speed based on the relative position. There is a desired constant distance d_{des} between the phantom vehicle and the first vehicle, which can be described as:

$$x_{\text{pha}}(t) = x_1^a(t) + d_{\text{des}} \tag{18}$$

where $x_{\text{pha}}(t)$ is the position of the phantom vehicle. The speed of the phantom vehicle depends on the longitudinal position and the relative speed of the first CAV.

The leading vehicle decisions depend on the following two conditions:

- The distance between the *Pre* and the first vehicle is less than the desired distance $d_{\text{safety}}^{\text{pre}}$:

$$x_1^a(t) + d_{\text{safety}}^{\text{pre}} \geq x_{\text{pre}}(t). \tag{19}$$

- The speed of the *Pre* is slower than the phantom vehicle at the current time step:

$$v_{\text{pha}}(t) \geq v_{\text{pre}}(t) \tag{20}$$

  where $v_{\text{pha}}(t)$ and $v_{\text{pre}}(t)$ are the speeds of the phantom vehicle and the *Pre*, respectively.

The leading vehicle makes decisions in real-time based on the above conditions. Meanwhile, the mixed platoon will follow the *Pre* only if all of the above conditions are satisfied.

B. Local Adaptation

Local adaptation involves controlling each CAV in the platoon and influencing the HDVs within the platoon. The time-based point-mass model (2) is used to represent the CAV's dynamics. The motion of HDVs within the HDV sub-platoon can be predicted by the NCM. Thus, the CAV tracks the reference speed with a high certainty condition based on the motion vector of the preceding HDV sub-platoon. The influence of the HDV sub-platoon is reduced for the following CAVs. The speed tracking MPC optimisation is formulated as:

$$\min \sum_{p=0}^{N_t-1} \|(v_{H+1}^a(t+p) - v_{\text{ref}}(t+p))\|^2 \tag{21}$$

subject to:

$$\begin{aligned} a_{H+1}^{a,\min} &\leq a_{H+1}^a(t+p) \leq a_{H+1}^{a,\max}, \forall p \in \{0,1,...,N_t-1\} \\ v_{H+1}^{a,\min} &\leq v_{H+1}^a(t+p) \leq v_{H+1}^{a,\max}, \forall p \in \{0,1,...,N_t-1\} \end{aligned} \tag{22}$$

where the cost function (21) represents the cumulative speed deviations between CAVs with the reference speed. The positive integer N_t is the prediction horizon. Since the CAV is influenced by the preceding HDV, traffic safety restrictions are necessary. The CAV should maintain a safe distance from the preceding HDV, which can be achieved via imposing the following constraint

$$d_{\text{safety}} + \Delta_{t_x} \cdot v_{H+1}(t) \leq x_H^h(t) - x_{H+1}^a(t) \tag{23}$$

where d_{safety} is the safety distance to avoid collisions at low vehicle speeds. Δ_{t_x} is the safe headway.

The min-max MPC for the CAV within a mixed platoon is focused on the car following performance and platoon stability, hence the min-max MPC with a prediction horizon N_t is formulated as:

$$\begin{aligned} \min\max\Bigg(&\|\Delta x_{i,e}(t+N_t)\|^2 + \sum_{p=0}^{N_t-1} (\|(z(t+p))\|^2 \\ &- \gamma^2 \|(d(t+p))\|^2) \Bigg) \end{aligned} \tag{24}$$

subject to:

$$\begin{aligned} a_i^{\min} &\leq a_i^a(t) \leq a_i^{\max} \\ e_{x,i}^{\min} &\leq \Delta p_i^a(t) \leq e_{x,i}^{\max} \\ e_{v,i}^{\min} &\leq \Delta v_i^a(t) \leq e_{v,i}^{\max} \\ a_i^{\min} &\leq a_{i-1}(t) \leq a_i^{\max} \end{aligned} \tag{25}$$

where $\forall p \in \{0,1,...,N_t-1\}$. The $z(t+p)$ is a performance metric to balance the stabilising performance of system states $\Delta x_e(t+p)$ and the control effort $u(t+p)$, which can be described as:

$$z(t+p) = C_z \Delta x_e(t+p) + D_z u(t+p) \tag{26}$$

where C_z and D_z are the coefficients given in (19) in our previous work [30]. The third term of (24) is the disturbance attenuation term, while the variable $d(t+p)$ is the disturbance introduced from the acceleration of vehicle $i-1$. γ is a self-defined non-negative scalar. The use of the disturbance attenuation term is important in two aspects: First, it ensures the robustness of the platooning errors $z(t)$ (i.e., relative velocity and spacing error) against the disturbance $d(t)$ (i.e., velocity changes of the preceding vehicle); Second, it ensures the ℓ_2 string stability of the platoon. By including the disturbance attenuation term, the min-max MPC cost function of (24) is equivalent to a ℓ_2-norm cost function and thus leads to the proof of the ℓ_2 string stability. The $e_{x,i}^{\min}$ and $e_{x,i}^{\max}$ are the minimal and maximal allowable inter-vehicle space errors, respectively. $e_{v,i}^{\min} = v_{i-1}(t) - v_{\max}$ and $e_{v,i}^{\max} = v_{i-1}(t) - v_{\min}$ are the maximal and minimal allowable inter-vehicle speed errors, respectively. The platoon error system based on time-based point-mass model (3) is used to represent the dynamics of CAV. The CAV within each CAV sub-platoon is designed to follow the first CAV in the sub-platoon rather than the first CAV within the entire platoon.

C. Platoon Stability

In this study, the collision avoidance between the CAV sub-platoon and the HDV sub-platoon is guaranteed by implementing the constraint (23) in the speed tracking MPC. Since the HDV sub-platoons within mixed platoons cannot be controlled directly, it is not easy to prove the absolute stability of the entire platoon. Hence, it is more realistic to consider the head-to-tail string stability of a mixed platoon [31]. The head-to-tail string stable indicates that the amplitude of oscillation at the first vehicle is not amplified on the last vehicle, regardless the behaviour of HDVs within the platoon. The head-to-tail string stable for a mixed platoon can be ensured if all CAV sub-platoons are head-to-tail string stable. In this study, the CAV sub-platoon control considers the ℓ_2 string stability [30]. To enable the min-max MPC directly quantify the ℓ_2 string stability metric, the ℓ_2-norm cost function has been used in the optimisation problem. The CAV sub-platoon is head-to-tail string stable in the sense of ℓ_2 string stability [10]. Therefore, the proposed mixed platoon is string stable. In the authors' previous work [30], details of the min-max MPC design were presented, where the string stability of the platoon control using the min-max MPC was also proved. Since this study focuses on eco-driving for mixed platoons, the analysis of ℓ_2 string stability will not be repeated.

VI. Simulations

In this section, simulations based on real traffic environments are carried out to validate the performance of the proposed eco-driving strategy for mixed platoons.

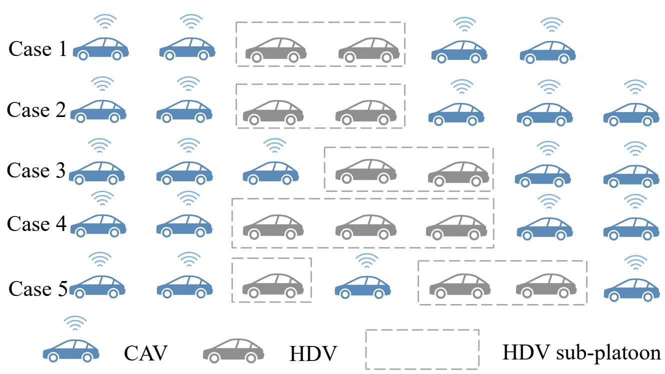

Fig. 6. The platoon configuration for simulation.

A. Simulation Setup

This study created simulation environments based on the road I-580 in California and traffic data provided by the PeMS [47]. The simulation environments include a motorway of 22,200 meters. The mixed platoons with the eco-driving strategy were simulated via *MATLAB* and *Autonomie* [48]. The MPC was modeled and solved using the tools *YALMIP* [49] and *MOSEK* [50]. Five mixed platoons are selected in this study as shown in Fig. 6. All the vehicles shown in Fig. 6 are within the platoon, and Case 2 and Case 3 contain identical vehicles with different orders in the platoons. Case 4 and Case 5 contain identical vehicles with different orders in the platoons. These cases comprehensively compare the performance of each strategy by different penetration rates and locations of HDV. Case 2 and Case 3 compare the impact of the HDV sub-platoon in different locations. Case 2 and Case 4 compare the effects of different numbers of HDV within the HDV sub-platoon. Case 4 and Case 5 compare the impact of different numbers of HDV sub-platoons. In order to accurately evaluate the performance of the proposed method and improve the credibility of simulation results, two different car-following models, NCM and FVD models, are used in this paper. The proposed eco-driving strategy applies the NCM to describe the motion of HDVs within the mixed platoon. In the simulation, the HDVs in all strategies follow the FVD model. The deployed model is different to the one used in controller design and therefore makes the evaluation more authentic. The proposed strategy was compared with two eco-driving benchmark strategies and a conventional adaptive cruise control strategy under the same conditions.

The three benchmark strategies are

- Vehicles using conventional-adaptive cruise control to follow each other is denoted as *ACC*. *ACC* is for a vehicle without communication to follow the desired speed and maintain a safe distance from the vehicle in front.
- CAVs using eco-adaptive cruise control to follow each other is denoted as *eco-ACC*. This benchmark strategy is designed to optimise the CAV individually. The *eco-ACC* based on the MPC controls the CAVs to maintain a safe distance from the vehicle in front and minimises the total energy by adapting their speeds in real-time. None of the vehicles using this strategy communicates with each other.
- CAVs using eco-cooperative adaptive cruise control to follow each other is denoted as *eco-CACC*. This benchmark strategy is designed to optimise the pure CAV platoon. The leader optimises the platoon total energy by adapting the speed based on an MPC. The distributed MPC is applied to the rest CAVs to track the leader in real-time. For example, Case 3 contains two CAV platoons, while the first three CAVs form one platoon and the last two CAVs form another platoon.

The proposed strategy optimises the energy consumption of the entire platoon, while the benchmark strategies only optimise the energy consumption of the controlled vehicles. All platoon strategies were tested in at least five different scenarios with the same average speeds of road, but with different traffic densities and flows.

B. Curve Matching Algorithm Evaluation

TABLE I
RMSE of the speed prediction error for the preceding vehicle with different HDV models.

Name of HDV model	FVD	IDM	OVM
RMSE (m/s)	0.1448	0.1553	0.1328

In online tracking, a CAV that follows the HDV can predict the motion of the HDV to improve tracking performance based on the NCM motion vector of time lag and space lag. The performance of NCM predicting the motion of the preceding HDV driven by different HDV models has been evaluated by the root mean square error (RMSE) and shown in TABLE

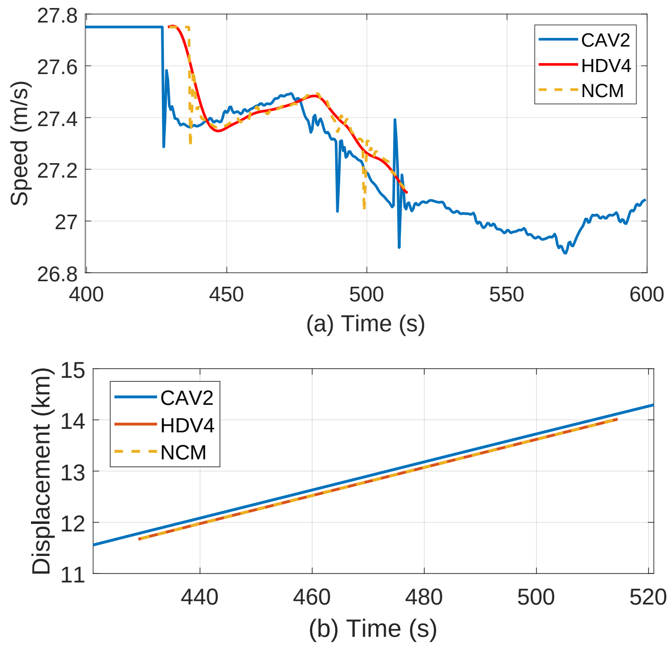

Fig. 7. The speed trajectories of HDV4 and CAV2 (a) and distance trajectories of HDV4 and CAV2 (b).

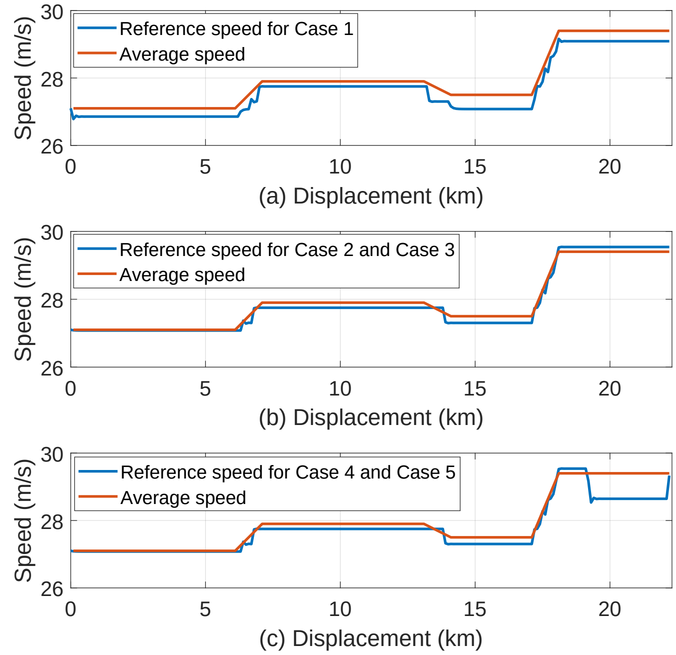

Fig. 8. Speed reference for Case 1 (a), for both Case 2 and Case 3 (b) and for both Case 4 and Case 5 (c).

I. The RMSE calculates the average error between the NCM prediction speed trajectory and speed trajectories of different HDV models. The results show that the NCM can accurately predict the motion of HDV driven by different HDV models. The HDV in the simulation is controlled by FVD model. An example based on the platoon in Case 1 is shown in Fig. 7. CAV2 receives a part of HDV4's speed trajectory data from CAV5, which travels according to the FVD model and is represented by the red curve in Fig. 7 (a). The blue curve represents the speed trajectory of CAV2. Therefore, the motion vector can be found using the curve matching algorithm. The yellow dotted curve represents the CAV2 iteratively moving the paired speed trajectory in accordance with the motion vector. The NCM provides an accurate motion vector so that the two speed trajectories almost coincide. However, the HDV is not sensitive to subtle accelerations and rapid speed changes. Thus, the speed trajectory of the HDV is smoother than that of the CAV. The displacement of the two trajectories also coincides as shown in Fig. 7 (b). The curve matching algorithm based on TCDs can identify an accurate motion vector for the HDV. Meanwhile, the HDV speed trajectory with a range of shape deformations does not influence the performance of the curve matching algorithm.

C. Road Test Simulation

Offline planning provides a speed reference for a mixed platoon based on the characteristics of each vehicle and the future traffic information. The platoon receives the average speed for the testing road segment via V2I communications. The speed references for each mixed platoon are shown in Fig. 8. The speed references are different for each mixed platoon because the vehicle characteristics vary. As mentioned earlier, the vehicles within the platoon are assumed to be travelling at the same speed in the offline planning stage, and the vehicles in Case 2 and Case 3 are identical. Therefore, Case 2 and Case 3 share the same reference speed. Meanwhile, for the same reason Case 4 and Case 5 share the same reference speed. Online tracking controls the mixed platoon, follows the reference speed and maintains the stability in real-time. The actual energy efficiency is influenced by the speed tracking performance. Therefore, each strategy is applied to each case and tested in various traffic scenarios to provide a more cogent result. In this paper, only speed trajectories with distinct characteristics are discussed and the energy efficiencies over all simulations are summarised.

The results of the proposed eco-driving strategies for Case 1 are depicted in Fig. 9. The blue curves are the reference speeds. Fig. 9 (a) shows the controlled mixed platoon with less disturbance from the *Pre*. The mixed platoon was able to track the reference speed for the entire trip. Details of mixed platoon Case 1 with less disturbance between 465 s and 519 s are shown in Fig. 9 (b). CAV5 equipped with speed tracking MPC has a more flexible inter-vehicle distance. As long as the inter-vehicle distance is longer than the minimum safe distance, CAV5 will follow the reference speed. Meanwhile, the motion of HDV4 can be predicted based on the motion vector and the speed trajectory of CAV2. Therefore, CAV5 and CAV6 have been decelerated at 489 s, which is before the preceding vehicle HDV4 to achieve a better reference speed tracking performance whilst maintaining a safe distance. The results of the proposed strategy and benchmark strategies for Case 1 with large disturbances from the *Pre* are shown in Fig. 10. The mixed platoon has the same traffic situation with each strategy. The Fig. 10 (a) shows the mixed platoon controlled by the proposed strategy. The *Pre* travelled at a slower speed

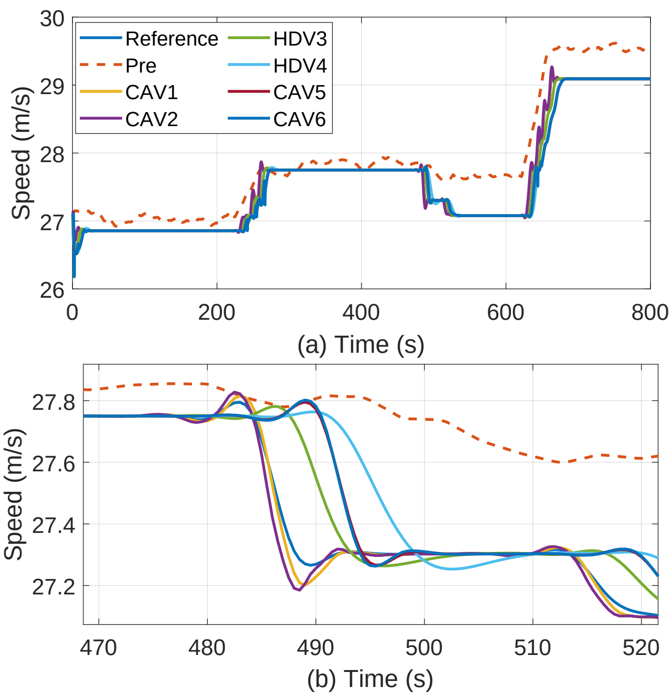

Fig. 9. Mixed platoon Case 1 controlled by the proposed strategy (a) and the details of Case 1 (b) with less disturbance.

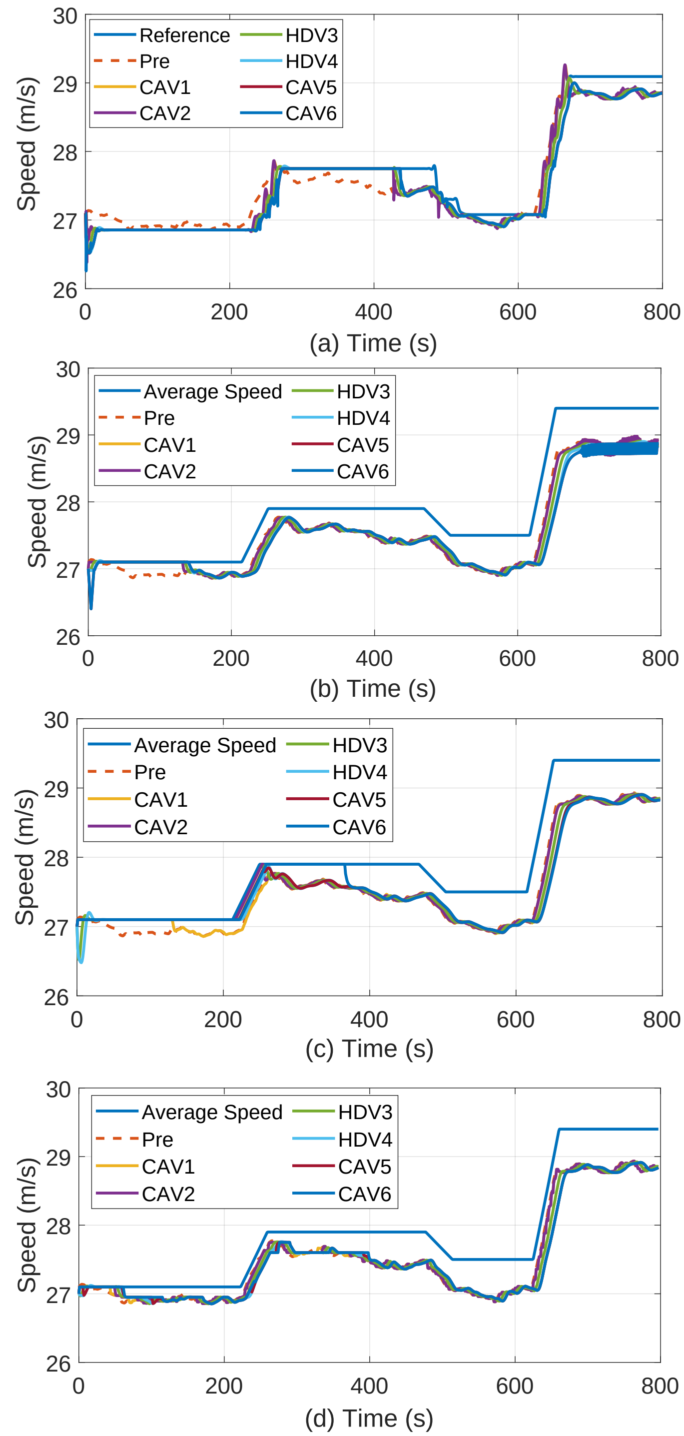

Fig. 10. Mixed platoon Case 1 controlled by the proposed strategy (a), the *eco-CACC* (b), the *eco-ACC* (c) and the *ACC* (d) with large disturbances, respectively.

than the reference speed from 273 s. Accordingly, the inter-vehicle distance between CAV1 and the *Pre* was reduced to the desired distance. Thus, the platoon started to follow the *Pre* from 472 s to the end of the trip. The result of *eco-CACC* for Case 1 with the same traffic situation is shown in Fig. 10 (b). CAV1 and CAV2 form a platoon, and CAV5 and CAV6 form another platoon. The platoons travelled with a Pulse and Glide (P&G) operation strategy [42] starting with the 690 s to the end. The P&G operation improved the vehicle's energy efficiency at the acceptable speed range. The result of *eco-ACC* strategy of Case 1 is shown in the Fig. 10 (c). The vehicles in the group control themselves without communication between each other. Unlike the proposed strategy of tracking the reference speed, a vehicle equipped with *eco-ACC* improves the energy efficiency by minimising unnecessary acceleration. Therefore, the speed trajectory of a vehicle with *eco-ACC* from 472 s to 670 s was smoother than proposed strategy as shown in the Fig. 10 (a). Same as the *eco-ACC*, the vehicles in the group control themselves under the *ACC* strategy are shown in Fig. 10 (d). However, because the *ACC* only focuses on the inter-vehicle distance maintenance, the speed of a vehicle with *ACC* is not smooth. The target speed of benchmark strategies are average speed. The relative vehicles position for Case 1 controlled by the proposed strategy and benchmark strategies with large disturbances are shown in Fig. 11 (a) to Fig. 11 (d), respectively. The curves in Fig. 11 (a) represent each vehicle's inter-vehicle distance to the leader vehicle provided by the leader vehicle decision. The curves in Fig. 11 (b) - Fig. 11 (d) represent each vehicle's inter-vehicle distance to the vehicle ahead of the platoon. As HDVs have a longer response time, the inter-vehicle distance of HDVs are large than CAVs in all strategies. The proposed strategy and the *eco-CACC* have similar results, which maintain the desired inter-vehicle distance. However, the inter-vehicle distance for *eco-ACC* is unstable. The CAV reduced the inter-vehicle distance to achieve better energy efficiency. The *ACC* has the largest inter-vehicle distance because eco-driving does not take into account in this strategy. The *ACC* only focuses on maintaining the desired inter-vehicle distance.

The example speed trajectories for the rest of the cases

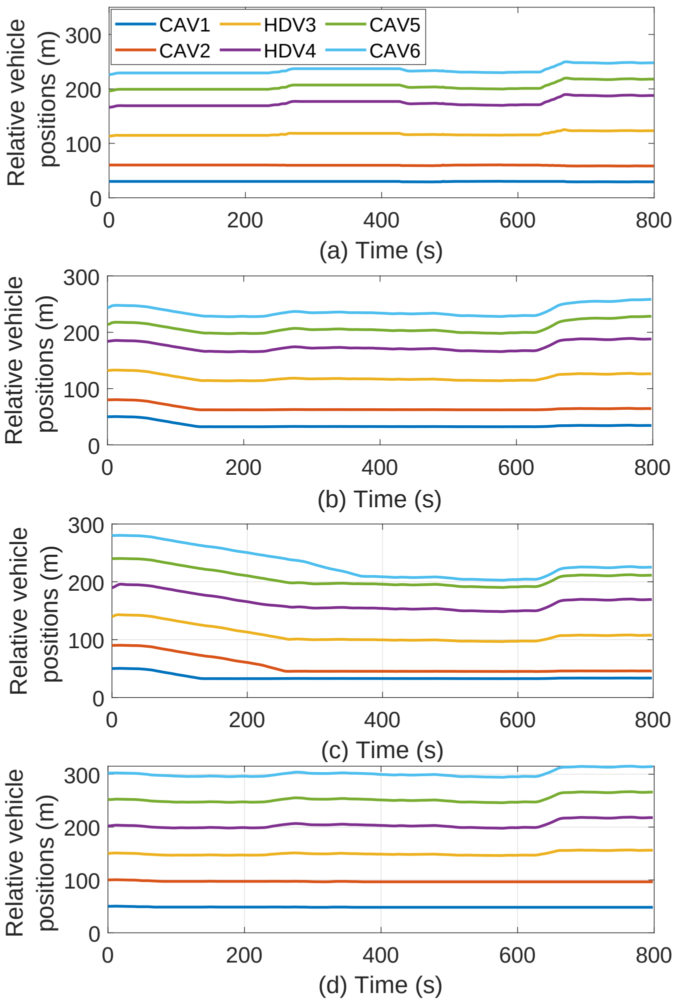

Fig. 11. Relative vehicle positions for Case 1 controlled by the proposed strategy (a), the *eco-CACC* (b), the *eco-ACC* (c) and the *ACC* (d) with large disturbances, respectively.

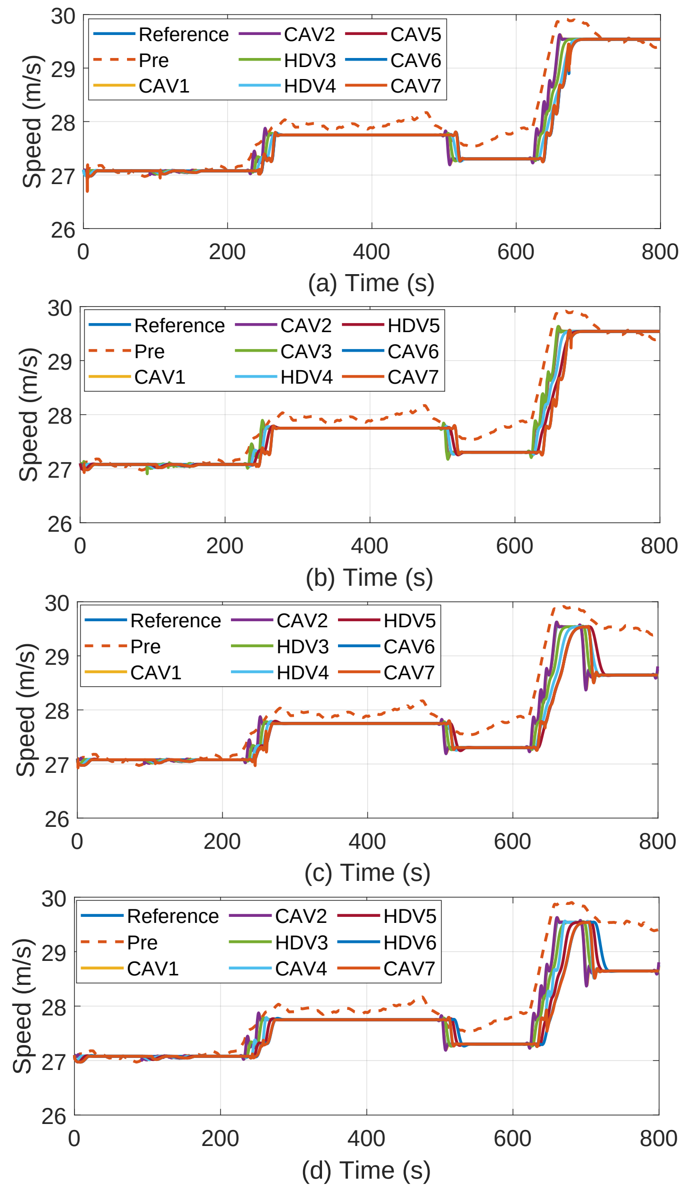

Fig. 12. Speed trajectories for mixed platoon Case 2 (a), Case 3 (b), Case 4 (c) and Case 5 (d).

are shown in Fig. 12. These four sub-plots in Fig. 12 (a) to Fig. 12 (d) are Case 2 to Case 5, respectively, and they travel in the same traffic conditions. In this traffic situation, the mixed platoon was influenced by the *Pre* between about $90\,\mathrm{s}$ and $170\,\mathrm{s}$. In Case 1 to 3, the CAVs behind the HDV sub-platoon were able to track the reference speed based on the motion vector of the HDV. In Case 4, CAV6 and CAV7 were not able to track the reference speed from $645\,\mathrm{s}$ to $700\,\mathrm{s}$. As the number of HDVs increased, the accuracy of the HDV motion prediction based on NCM decreased. The predicted acceleration of HDV5 is higher than the actual acceleration at $634\,\mathrm{s}$. Thus, the inter-vehicle distance between CAV6 and HDV5 dropped to a safe distance at $645\,\mathrm{s}$. In Case 5, the number of HDVs within the platoon is the same as in Case 4. However, these HDVs are in two different HDV sub-platoons. As the CAV4 is between two HDV sub-platoons, the cumulative speed error by the HDV sub-platoon is less than in Case 4. Hence the HDV's impact on CAV7 is not as strong as the last CAV sub-platoon in Case 4. However, in general, the increase in the number of HDVs deteriorates the speed tracking accuracy of the following CAVs.

D. Fuel Consumption

A bar graph is included in Fig. 13 to compare the fuel economy between the platoons with the proposed strategy and the benchmark strategies. The average fuel consumption for each platoon case that followed a different strategy is illustrated. In each sub-set, the proposed strategy, the *eco-CACC*, the *eco-ACC* and the *ACC* are represented in blue, red, yellow and purple, respectively. The vehicle configurations in Case 2 to Case 5 are the same. Among the four cases, the mixed platoon that is equipped with the proposed strategy had the best energy efficiency in Case 3, and the highest fuel consumption in Case 4. Platoon Case 3 has the largest number of CAVs ahead of the HDV sub-platoon, and a dominant number of CAVS in the platoon. Therefore, the reference speed tracking performance was the best in this case. In contrast, as the number of HDVs increased, the tracking errors in Case 4 and Case 5 also increased. In Case 4, CAV6 and CAV7 could not track the reference speed, even if the platoon was not influenced by other traffic participants. The *ACC* strategy had the highest fuel consumption for each case, while the results of the proposed strategy and the *eco-CACC* were relatively similar. However, the HDV energy efficiency improved with the proposed strategy. Compared with the *eco-CACC*, *eco-ACC* and *ACC* strategies, the total fuel consumption of the proposed strategy was reduced by 1.15%, 2.98% and 6.39% respectively. Overall, the proposed strategy for platoons demonstrated better energy efficiency than the other strategies.

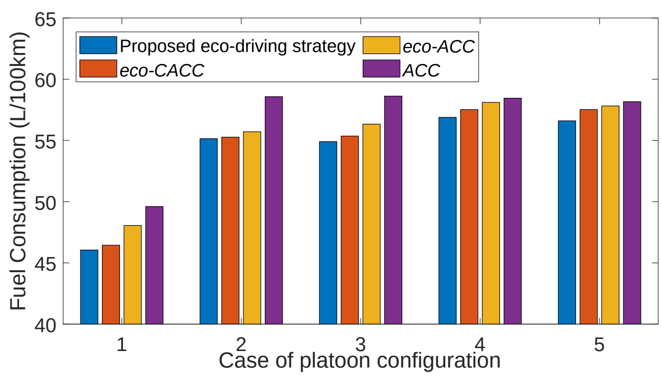

Fig. 13. The average fuel consumption of each case under different control strategies.

VII. Conclusion

Focusing on the platoon in mixed traffic, this paper proposes an eco-driving strategy for mixed platoons in general structures. The target of the platooning is to achieve minimum total fuel consumption. The offline planning creates a reference speed for mixed platoons based on vehicle characteristics and traffic data for future routes. The selfish optimisation of the offline planning has been avoided based on the speed deviation minimisation contained in the optimisation. Moreover, the eco-driving optimised the speed of the mixed platoon based on the engine fuel efficiency map extracted from each CAV with physical constraints. Therefore, the reference speed is more feasible to be applied in practical driving. This paper uses the NCM based on the curve matching algorithm to describe and predict the dynamics of HDVs within the platoon. Hybrid distributed MPC was designed for platoon control to improve the speed tracking performance and maintain the platoon's stability. The simulation results show that the penetration rates of HDVs and the order of vehicles influence the performance of energy optimisation. The energy optimisation effect is reduced, when penetration rates of HDVs increase or the location of the HDV sub-platoons is closer to the head of the platoon. Hence, eco-driving may not be able to optimise platoons that have high HDV penetration rates. In the future, eco-driving models and control methods for platoons with high HDV penetration rates and multiple HDV sub-platoons will be developed. Moreover, the proposed eco-driving mixed platoon will be verified in real world testing.

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