Platoon Centered Control for Eco-driving at Signalized Intersection Built upon Hybrid MPC System

Hanyu Zhang
Department of Civil and Coastal Engineering,
University of Florida, Gainesville, Florida, USA
Email: Hanyu.zhang@ufl.edu

Lili Du*
Department of Civil and Coastal Engineering,
University of Florida, Gainesville, Florida, USA
Email: lilidu@ufl.edu

***Abstract*— Even though extensive studies have developed various eco-driving strategies for vehicle platoon to travel on urban roads with traffic signals, most of them focus on vehicle-level trajectory planning or speed advisory rather than real-time platoon-level closed-loop control. In addition, majority of existing efforts neglect the traffic and vehicle dynamic uncertainties to avoid the modeling and solution complexity. To make up these research gaps, this study develops a system optimal vehicle platooning control for eco-driving (SO-ED), which can guide a mixed flow platoon to smoothly run on the urban roads and pass the signalized intersections without sudden deceleration or red idling. The SO-ED is mathematically implemented by a hybrid model predictive control (MPC) system, including three MPC controllers and an MINLP platoon splitting switching signal. Based on the features of the system, this study uses active set method to solve the large-scale MPC controllers in real time. The numerical experiments validate the merits of the proposed SO-ED in smoothing the traffic flow and reducing energy consumption and emission at urban signalized intersections.**

***Keywords*— eco-driving, vehicle platoon, model predictive control, hybrid control system, signalized intersection**

I. Introduction

In recent years, inspired by the rapid advancement of connected and autonomous vehicle (CAV) technologies, various eco-driving strategies and algorithms have been developed for urban traffic intersections, aiming to improve traffic safety and efficiency while reducing fuel consumption and emission. The schemes of the related studies show two main streams: (i) vehicle-level speed advisory, which provides offline (*1, 2*) or online (*3*) speed advice for individual vehicles; (ii) platoon-level eco-driving strategy, which develops trajectory planning for the entire platoon as a system (*4-8*). The existing studies (*9*) showed that the platoon-level eco-driving strategies perform better. It thus attracts tremendous research interest in literature and also motives this effort. Nevertheless, we notice the following research gaps and then involve the enhanced features as follows.

First of all, most of the existing eco-driving strategies focus on vehicle trajectory planning or speed advice (*4-8*). Although showing improved performance in saving energy consumption and reducing emission, this type of planning scheme usually cannot adapt to the trajectory derivation due to various uncertain factors. Accordingly, many studies work on a pure CAV traffic flow (*4-6*) to reduce uncertainty. In addition, most eco-driving algorithms use deterministic double-integrator model to capture vehicle movement dynamics, ignoring powertrain delay, aerodynamic drag, etc. Those simplifications will discount the applicability of those approaches in reality. Nevertheless, integrating these uncertainties into the eco-driving strategies will lead to nonconvexity of control model. Consequently, it brings in tremendous difficulty in theoretical analysis and solution approach development. This study intends to partially bridge this gap by developing a robust model predictive control (MPC).

This study also noticed that most of the existing platoon-level eco-driving strategies only optimize the leading vehicle's trajectory while implementing adaptive cruise control (ACC) or cooperative adaptive cruise control (CACC) for the rest following vehicles (*4,6*). Clearly, these types of eco-driving cannot guarantee platoon's system performance. In view of this issue, this study develops a platoon-centered vehicle platooning control scheme to overcome this weakness. However, these merits company with new challenges, particularly for this study. The platoon-centered vehicle platooning often involves a large-scale optimizer, which must be solved within a control interval (< 1 second). In addition, existing platoon-centered vehicle platooning applies (*10*) a constant spacing policy to facilitate control stability, which leads to low-capacity usage and does not fit the urban road scenario. This study thus develops a new platoon-centered vehicle platooning control with adaptive spacing policy and then uses an active set method based on the problem features to address those challenges.

Furthermore, a long platoon usually cannot completely pass the intersection within one green interval. Then, how to properly split a long platoon so that those sub-platoons can pass intersection sequentially while adapting to the signal information represents a common challenge for many eco-driving strategies. Most of existing splitting schemes in the literature (*5,6,8*) use simple heuristic rules aiming to maximize traffic throughputs without considering traffic smoothness. This study intends to develop an optimal platoon spitting scheme holistically considering traffic throughput, smoothness, and energy consumption.

To enable efficient eco-driving while factoring all the enhanced features discussed above, this study develops an efficient system optimal platoon-based eco-driving control (SO-ED) scheme at signalized intersection. It instructs a mixed flow platoon to smoothly and efficiently approach and then pass signalized intersections while avoiding red idling as much as possible. The development of the SO-ED contributes the following methodologies. First of all, this SO-ED is modeled as a hybrid MPC system involving three MPC controllers, which respectively generate optimal control laws for the platoon to approach, split, then pass intersection. A mixed integer nonlinear programming optimizer (MINLP) is used to determine the optimal platoon splitting point and functions as a switching signal to connect the MPC controllers in the hybrid system. The MPC controllers and the switching signal MINLP together mathematically capture the dynamic control process when a platoon approaches an intersection, splits into sub-platoons and then sequentially passes the intersection during different green intervals. We developed an active set method to solve the MPC controllers efficiently. Our experiments showed the proposed SO-ED can ensure the traffic smoothness and significantly reduce the energy consumption and emission at the signalized intersection.

II. Problem Statement

This study considers a sample mixed-flow platoon moving toward a signalized intersection on an urban road in Figure 1. The sample platoon follows a leading HDV $\hat{0}$. Then it contains three sequential platoon segments: a CAV platoon segment C_1 including n CAVs, a HDV platoon segment H including $\hat{m}$ HDVs, and then a CAV platoon segment C_2. Within a CAV platoon, we consider a general preceding-and-following communication network topology.

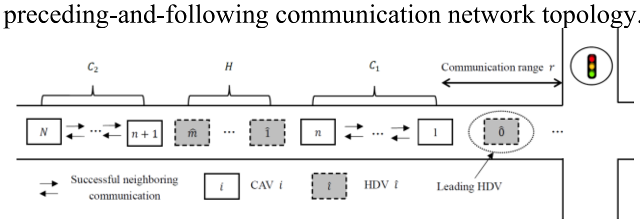


Figure 1. Sample platoon at the signalized intersection

To mathematically model the proposed study, we use notations x_i, v_i u_i for $\forall i \in I_C = \{1, \dots, N\}$ and $x_{\hat{\imath}}$, $v_{\hat{\imath}}$ $u_{\hat{\imath}}$ for $\forall \hat{\imath} \in I_H = \{\hat{0}, \hat{1}, \dots, \hat{m}\}$ to represent the longitudinal position, speed, and acceleration of the i_{th} CAV and the $\hat{\imath}_{th}$ HDV respectively. The platoon control is conducted at discrete time steps (indexed by $k \in \mathbb{Z}_+ := \{0,1,2, \dots\}$) with a control time interval $\tau > 0$. Control inputs u_i $(i \in I_C)$ keep constant during an interval τ. For notational simplicity, we use $x_i(k)$, $v_i(k)$ $u_i(k)$ to substitute $x_i(\tau k)$, $v_i(\tau k)$ $u_i(\tau k)$ hereafter. When the leading platoon segment C_1 reaches the communication zone, namely r distance from the traffic signal, it will acquire and receive the real-time traffic signal information. This study assumes the traffic signal is in green phase when the platoon reaches the communication zone. The real-time traffic signal information includes green and red phase intervals $\tau k_g / \tau k_r$ as well as the remaining time of the current phase, such as the remaining green interval assumed in this study denoted by $\tau \tilde{k}_g$.

In reality, a long platoon may not be able to pass an intersection during the current green interval. As a result, the platoon needs to split into several sub-platoons to sequentially pass the intersection during consecutive traffic signal cycles. To make the platoon driving adaptive to this scenario, this study develops a mixed integer non-linear programming optimizer (MINLP) to find the optimal platoon splitting point. It predicts the platoon's future movements and intends to ensure the traffic smoothness while sustaining the maximum traffic throughputs. Following the optimal platoon splitting point, two different control laws are developed to guide the platoon splitting and instruct the first sub-platoon A_1 and second sub-platoon A_2 respectively to smoothly pass the intersection in the sequential green intervals.

III. Mathematical Model

This section first introduces vehicle dynamics and associated constraints, factoring the uncertainty at each control time step $k \in \mathbb{Z}_+$. Considering vehicles' powertrain delay and aerodynamic drag are stochastic and time-variant, this study adopts the robust double-integrator model in (1) and (2) to describe CAV i's dynamics, $i \in I_C$.

$$x_i(k+1) = x_i(k) + \tau v_i(k) + \frac{\tau^2}{2}\big(u_i(k) - \Delta u_i(k)\big), \tag{1}$$

$$v_i(k+1) = v_i(k) + \tau\big(u_i(k) - \Delta u_i(k)\big), \tag{2}$$

where $\Delta u_i(k)$ factors vehicle's powertrain delay and aerodynamic drag by (3), which was developed by (*11*).

$$\Delta u_i(k) = \varepsilon_i v_i(k) + \eta_i u_i(k) - \eta_i u_i(k-1) \tag{3}$$

The movements of HDVs are described by Newell's car-following model (*12*) in (4),

$$x_{\hat{\imath}}(k) = x_{\hat{\imath}-1}(k - t_{\hat{\imath}}) - d_{\hat{\imath}}, \hat{\imath} \in I_H, \tag{4}$$

where $t_{\hat{\imath}}$ and $d_{\hat{\imath}}$ represent the time and distance displacement of the HDV $\hat{\imath}$. It considers the time-distance trajectory of the following vehicle is essentially the same with the leading vehicle except a time and distance displacement.

Furthermore, we consider the CAV control input, speed and the safety distance need to satisfy the physical constraints shown in (5), (6) and (7) respectively.

$$a_{min,i} \leq u_i(k) \leq a_{max,i}, \tag{5}$$

$$v_{min} \leq v_i(k) \leq v_{max}, \tag{6}$$

$$\begin{aligned} x_{i-1}(k) - x_i(k) \geq L_i + \delta_1 \tau v_i(k) \\ + \delta_2 \tau \big(v_i(k) - v_{i-1}(k)\big) \end{aligned} \tag{7}$$

Here $a_{max,i}$ and $a_{min,i}$ are used to describe the predefined acceleration/deceleration bounds for i_{th} CAV in platoon. v_{min} and v_{max} are the pre-specified bounds on longitudinal speed for i_{th} CAV in platoon. Regarding the driving safety, an adaptive safe distance is enabled by (7), which considers the safe time headway and the speed difference between leading and following vehicles to ensure the safety and improve the traffic throughputs.

According to the adaptive safety constraints, this study uses the adaptive desired spacing policy in (8), which will be used in the objective function of the MPC control.

$$s_i(k) = L_i + \delta_1 \tau v_i(k) + \delta_2 \tau \big(v_i(k) - v_{i-1}(k)\big) + \delta, \tag{8}$$

where $s_i(k)$ represents the desired spacing for CAV i at step k. Positive $\delta > 0$ is introduced to make the desired spacing $s_i(k)$ slightly larger than the safe car-following distance in (7).

Accordingly, we define the CAV i's spacing and speed errors in (9) and (10) respectively as follows.

$$\Delta x_i(k) = x_{i-1}(k) - x_i(k) - s_i(k), \qquad i \in I_C, \tag{9}$$

$$\Delta v_i(k) = v_{i-1}(k) - v_i(k), \qquad i \in I_C, \tag{10}$$

Next, built upon the spacing and speed error terms in (9) and (10), the platoon control dynamics are summarized in (11) and (12).

$$z(k) \coloneqq \big(\Delta x_1(k), \ldots, \Delta x_N(k)\big)^T \in \mathbb{R}^N, \tag{11}$$

$$z'(k) \coloneqq \big(\Delta v_1(k), \ldots, \Delta v_N(k)\big)^T \in \mathbb{R}^N. \tag{12}$$

IV. Hybrid MPC Model

The SO-ED is modeled as a hybrid MPC system, seeking to instruct the movement of a mixed flow platoon so that it can approach and then pass a signalized intersection smoothly. As shown in Figure 2, the platoon will experience three states to go through the intersection, respectively guided by three MPC controllers and three switching signals. Specifically, state q_0 represents the mixed flow platoon approaching the signalized intersection under the guide of MPC-q_0. Once the platoon enters the communication zone of the traffic signal, an MINLP optimizer is started to find the optimal platoon splitting point within one control interval (1 second), from which the SO-ED triggers the switching signal σ_0 to split the mixed flow platoon into two sub-platoons A_1 and A_2. After that, the SO-ED starts to implement q_1 and q_2 MPC controllers (MPC-q_1, MPC-q_2), which respectively guide the movements of sub-platoons A_1 and A_2 so that they can smoothly pass the intersection during the current or future green intervals. When the sub-platoons A_1 and A_2 passes or reach the intersection,

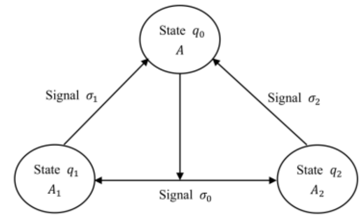


Figure 2. Hybrid MPC system controller

A. MPC controller for State q_0

This study considers the platoon is under a platoon-based car-following control approaching the intersection. Accordingly, we employ the following MPC-q_0 in (13) , subject to the vehicle dynamics and constraints (1)-(12) developed in Section III to conduct CAV trajectory control at any step $k \in \mathbb{Z}_+$ before the platoon enters the communication zone and trigger the signal σ_0. If there is no vehicle ahead leading the platoon, then the first platoon CAV $i = 1$ will be served as the leading vehicle and it will implement a controller to keep the desired speed. The technical details of this controller can be seen in Appendix I. Note that the following MPC is conducted at any time step $k + p$, $k \in \mathbb{Z}_+$. We simplify it to p hereafter throughout this section for simplifying notation purpose.

MPC-q_0

$$\textbf{Min}\ \Gamma\big(u(p)\big) = \sum_{p=1}^{P} \{\frac{1}{2}[z^T(p) Q_z z(p) + (z'(p))^T Q_{z'} z'(p)] + \frac{\tau^2}{2} \omega_1 \|u(p-1)\|_2^2\} \tag{13}$$

Subject to, for $p \in P$:

Constraints in (1)-(12),

where $Q_z \coloneqq \mathrm{diag}(\alpha_1, \ldots, \alpha_n)$ and $Q_{z'} \coloneqq \mathrm{diag}(\beta_1, \ldots, \beta_n)$ are diagonal matrices; $\alpha_i > 0$ and $\beta_i > 0$ are penalty weights of the spacing and speed errors for each CAV $i = 1, \cdots, n$. Note that this platoon-based car-following control is different from the existing system optimal vehicle platooning approach. It considers the control uncertainties as well as adaptive desired spacing policy for adapting to the urban traffic environment better. Using MPC-q_0, when the platoon enters the traffic signal communication zone, we assume the current traffic signal phase is green.

B. Switching signal σ_0 MINLP

Once a platoon enters the communication zone of traffic signal and triggers the splitting, we will use an optimizer to find the optimal splitting point within one control interval so that the successive MPC control (q_1 and q_2) can conduct motion control to optimally split the platoon into two sub-platoons A_1 and A_2 from the splitting point, and then guide them to sequentially pass the intersection during the consecutive green intervals. This section focuses on developing this optimizer, which is the switching signal σ_0 in the hybrid system for finding optimal splitting point. To do that, we introduce binary variable $y_i \in \{0,1\}, i \in \overline{I_c} = \{1,2,\dots,n,n+1,\dots N,N+1\}$ to describe the location of the platoon splitting point around CAVs in the platoon. For example, $y_{i^*}=1$ if the platoon splits immediately ahead of the CAV i^* and $y_{i^*}=0$ otherwise, $i^* \in \overline{I_c}$. Note that we only split the platoon ahead of a CAV since HDV is not under trajectory control.

Equation (14) below formally presents the binary variable constraints, restricting only one platoon splitting point exist in the mixed flow platoon since each time we split a platoon into two parts A_1 and A_2, and make sure A_1 can pass the intersection during the current green phase.

$$\sum\nolimits_{i\in\overline{I_c}} y_i = 1; y_i \in \{0,1\} \tag{14}$$

Given the first sub-platoon segment A_1 is ensured to pass the intersection in the current remaining green phase, namely within next $\tilde{k}_g$ time steps. Then, given the platoon is split before CAV i, then the last CAV $i-1$ in sub-platoon A_1 should pass the intersection before time step $p=\tilde{k}_g$. We present this consideration in (15) below. Note that the position of the signal is considered as longitude coordinate 0.

$$x_{i-1}(\tilde{k}_g) \geq -M(1-y_i), \quad i \in \overline{I_c} \tag{15}$$

On the other side, we regulate that the second sub-platoon segment A_2 cannot go through the intersection until the end of the red interval at time step $p=\tilde{k}_g+k_r$. We describe this requirement in (16), where $M>0$ is a big given positive number.

$$x_i(\tilde{k}_g+k_r) \leq M(1-y_i), \quad i \in \overline{I_c} \tag{16}$$

To split the platoon into two sub-platoons, we should enlarge the inter-vehicle spacing at the splitting point and consequently the speed difference at the platoon splitting point will also get larger. Accordingly, we modify the measures of spacing and speed errors at the platoon splitting point in the σ_0 Optimizer by (17) and (18).

$$\Delta x_i(p) = x_{i-1}(p) - x_i(p) - s_i(p) - y_i * \mathcal{D} \tag{17}$$

$$\Delta v_i(p) = v_{i-1}(p) - v_i(p) - y_i * \mathcal{D}' \tag{18}$$

where parameters $\mathcal{D}$ and in $\mathcal{D}'$ represent the estimated platoon splitting spacing and speed difference between two sub-platoons A_1 and A_2. Finally, we summarize the signal σ_0 Optimizer as follows.

Signal σ_0 MINLP

$$\textbf{Min } J(u,y) = J_1(u,y) + \omega_2 J_2(u,y) \tag{19}$$

Subject to, for $p \in P, i \in I$:

Constraints in (1)-(8), (11)- (12), (14)-(18),

where

$$J_1(u,y) = \sum_{p=1}^{P=\tilde{k}_g+k_r} \left\{ \frac{1}{2}\left[z^T(p)Q_z z(p) + \left(z'(p)\right)^T Q_{z'} z'(p)\right] + \frac{\tau^2}{2}\omega_1 \|u(p-1)\|_2^2 \right\}$$

$$J_2(u,y) = -\sum_{i\in I_c\cup\{n+1\}} i * y_i$$

The objective function J in (19) makes a tradeoff between the traffic smoothness and traffic throughputs by tuning weight ω_2. The first component $J_1(u,y)$ promotes traffic smoothness in the next $P=\tilde{k}_g+k_r$ steps, whereas the second component $J_2(u,y)$ considers maximizing the traffic throughputs. Overall, the signal σ_0 MINLP will figure out the optimal platoon splitting point by predicting future platoon control and movements, subject to safety and platoon splitting constraints. It aims to improve the traffic smoothness and efficiency while facilitating the platoon splitting.

C. MPC controller for State q_1

We next develop the MPC model for state q_1 (MPC-q_1). It guides the leading sub-platoon A_1 to smoothly pass the intersection in the current green interval. To do that, we denote the CAV set in the sub-platoon A_1 by the notation $\widehat{A_1}$. Then the sub-platoon A_1 should pass the intersection within the remaining green interval. Accordingly, we have the following constraint in (20) derived from the (15).

$$x_{i^*-1}(P) \geq 0, \tag{20}$$

where i^* represents the optimal platoon splitting point determined by the signal σ_0 Optimizer. P is the MPC-q_1 prediction horizon, where $P=\tilde{k}_g, \tilde{k}_g-1,\dots,1$ as the control proceeds. Below we summarize the optimizer of MPC-q_1 at each time step during the green interval.

MPC-q_1

$$\textbf{Min}\ \Gamma(u)=\sum_{p=1}^{P}\left\{\frac{1}{2}\left[z^T(p)Q_z z(p)+\left(z'(p)\right)^T Q_{z'}z'(p)\right]+\frac{\tau^2}{2}\omega_1\|u(p-1)\|_2^2\right\} \tag{21}$$

Subject to, for $i\in\widehat{A_1}, p\in P, P=\tilde{k}_g,\tilde{k}_g-1,\dots,1$:

Constraints in (1)-(12), (20).

Overall, MPC-q_1 regulates the trajectory control of the leading sub-platoon A_1 and guide it to pass the intersection during the current green interval while ensuring the platoon's system performance and traffic smoothness.

D. MPC controller for State q_2

We last develop the MPC controller for state q_2 (MPC-q_2). It instructs the latter sub-platoon A_2 to reach the intersection economically and smoothly by reducing or even avoiding the red idling. We denote the CAV set in the sub-platoon A_2 by the notation $\widehat{A_2}$. Then we present the CAVs' trajectory control at each step as follows in (22).

MPC-q_2

$$\textbf{Min}\ \Gamma(u)=\sum_{p=1}^{P}\left\{\frac{1}{2}\left[z^T(p)Q_z z(p)+\left(z'(p)\right)^T Q_{z'}z'(p)\right]+\frac{\tau^2}{2}\omega_1\|u(p-1)\|_2^2\right\} \tag{22}$$

for $i\in\widehat{A_2}, p\in P, P=\tilde{k}_g+k_r,\ \tilde{k}_g+k_r-1,\dots,1$:

Subject to Constraints in Equations (1)- (12), (23)

$$x_{i^*}(P)\le 0 \tag{23}$$

Where $P=\tilde{k}_g+k_r,\ \tilde{k}_g+k_r-1,\dots,1$ as the control proceeds. Equation (23) is derived from (16). It regulates that the sub-platoon A_2 cannot pass the intersection until the red interval runs out. Overall, MPC-q_2 describes the trajectory control of the latter sub-platoon A_2 and guide it to reach the intersection at the beginning of the next green interval. It aims to ensure the traffic throughputs and smoothness.

V. Solution Approach

To implement the hybrid MPC system above, we need to solve these MPC controllers and the signal optimizer MINLP efficiently within a control time interval (<1 sec) to ensure the control continuity. The long prediction horizon of these MPC controllers further leads to large-scale optimization problems and consequently poses tremendous difficulty in developing efficient numerical solvers. This section thus uses efficient optimization algorithms to solve the MPC-q_0, MPC-q_1, MPC-q_2 and the signal σ_0 MINLP in the hybrid MPC system. Specifically, the MINLP optimizer can be efficiently solved by the distributed branch and bound algorithm developed in (*13*). Then, we mainly focus on developing an active set algorithm (AS) to quickly solve the MPC controllers by taking advantage the unique features of this problem. Below we present the technical details of the active set algorithm.

The active set method is an important algorithm in optimization, as it determines which constraints will affect the final results of the optimization (*14*). The active method is widely used particularly in the optimization-based control problems because many control problems involve extensive redundant inequality constraints. Using active set method will remove these redundant inequality constraints and simplify the optimization problem. This study noticed that most of the constraints in the MPC controllers are inequality constraints, such as constraints in (5)-(7). Further, the experiments indicated that majority of the inequality constraints of the MPC controllers are not active[1] under normal traffic conditions. Using these problem features, this study considers using active set algorithm, which first neglects all the inequality constraints to solve the optimizer and then iteratively adds active constraints back. We summarize the procedure of the active set algorithm in Figure 3 below.

<u>Initialize</u> an empty Active set $AS=\emptyset$
<u>Repeat until</u> 'no infeasible constraints & negative Lagrange multipliers':
(1) Solve the Optimizer, subject to active set AS constraints
(2) Compute the Lagrange multipliers of the active set AS
(3) Remove constraints with negative Lagrange multipliers from active set AS
(4) Each CAV i searches for its own infeasible constraints and add to set AS.
<u>End repeat</u>

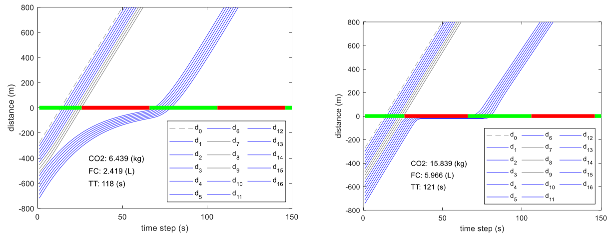
Figure 3. AS-OCD Outer loop (AS)

VI. Numerical Experiments

This study validates the traffic performance of the proposed SO-ED control when a platoon passes the intersection. The experiments compared the SO-ED with an existing CACC controller. The results are shown in Figure 4 below. Specifically, we set the remaining green interval equal to 25 seconds ($\tilde{k}_g=25$ s) when the mixed flow platoon with a HDV leading vehicle arrives at the communication zone (r =300 m away from the intersection). Then we set the green interval and red interval are 40 seconds in a traffic signal

[1] Given an optimization problem, an inequality constraint $g(x)\ge 0$ is called active at x if $g(x)=0$ and inactive at x if $g(x)>0$, whereas equality constraints are always active.

cycle: $k_r = k_g = 40$s. The experiment uses the VT-micro model to estimate the fuel consumptions and emissions (*15*).



(a) SO-ED ($\tilde{k}_g = 25$) (b) CACC ($\tilde{k}_g = 25$)

Figure 4. Distance-time trajectory (SO-ED and CACC)

Figure 4 indicates that the SO-ED control can significantly improve the traffic smoothness, save fuel consumptions and emissions as compared with the CACC control under both green and red scenarios. Mainly, the platoon using the SO-ED control in Figure 4 (a) will split into two sub-platoons to sequentially pass the intersection. It is noted that the latter sub-platoon will decelerate gently and smoothly to avoid red idling and reduce fuel consumption and emission. For the entire trip, SO-ED control can save approximately 59% fuel consumptions and CO2 emissions as well as 3 seconds total travel time for each vehicle, compared with CACC control in Figure 4 (b).

VII. Conclusion

This study develops a system optimal platoon-based eco-driving control (SO-ED), aiming to guide a mixed flow platoon to run on the urban roads smoothly and pass the signalized intersections economically. Different from the existing research focusing on the trajectory planning, a hybrid MPC system is used in this study to implement the SO-ED, which is a closed-loop control and adapts to CAV dynamic uncertainties. For the control continuity and online implementation, an active set algorithm is developed to solve large-scale MPC models efficiently. Numerical experiments are conducted to validate the performance of the SO-ED in smoothing traffic and reducing energy consumption and emission. There are several interesting future topics motivated by this study. One of them is to consider the signal control adaptive to the upcoming traffic flow. This extension may further smooth traffic and reduce energy consumption but brings in new challenges such as coordination issues of platoon and signal control. We propose to address these challenges in the future work.

Acknowledgments

This research is partially funded by National Science Foundation, award CMMI 1901994.

Reference

1. Alsabaan, M., Naik, K., Khalifa, T., 2013. Optimization of fuel cost and emissions using v2v communications. IEEE Transactions on intelligent transportation systems 14 (3), 1449–1461.
2. Yang, H., Jin, W.-L., 2014. A control theoretic formulation of green driving strategies based on inter-vehicle communications. Transportation Research Part C: Emerging Technologies 41, 48–60.
3. Wan, N., Vahidi, A., Luckow, A., 2016. Optimal speed advisory for connected vehicles in arterial roads and the impact on mixed traffic. Transportation Research Part C: Emerging Technologies 69, 548–563.
4. Wei, Y., Avcı, C., Liu, J., Belezamo, B., Aydın, N., Li, P. T., Zhou, X., 2017. Dynamic programming-based multi-vehicle longitudinal trajectory optimization with simplified car following models. Transportation research part B: methodological 106, 102–129.
5. Faraj, M., Sancar, F.E. and Fidan, B., 2017, June. Platoon-based autonomous vehicle speed optimization near signalized intersections. In *2017 IEEE Intelligent Vehicles Symposium (IV)* (pp. 1299-1304). IEEE.
6. Li, L.H., Gan, J. and Li, W.Q., 2018. A separation strategy for connected and automated vehicles: utilizing traffic light information for reducing idling at red lights and improving fuel economy. *Journal of Advanced Transportation*, *2018*.
7. Zhao, W., Ngoduy, D., Shepherd, S., Liu, R., Papageorgiou, M., 2018.A platoon based cooperative eco-driving model for mixed automated and human-driven vehicles at a signalised intersection. Transportation Research Part C: Emerging Technologies 95, 802–821.
8. Chen, C., Wang, J., Xu, Q., Wang, J. and Li, K., 2021. Mixed platoon control of automated and human-driven vehicles at a signalized intersection: dynamical analysis and optimal control. *Transportation Research Part C: Emerging Technologies*, *127*, p.103138.
9. Lioris, J., Pedarsani, R., Tascikaraoglu, F.Y. and Varaiya, P., 2016. Doubling throughput in urban roads by platooning. *IFAC-PapersOnLine*, *49*(3), pp.49-54.
10. Gong, S. and Du, L., 2018. Cooperative platoon control for a mixed traffic flow including human drive vehicles and connected and autonomous vehicles. *Transportation research part B: methodological*, *116*, pp.25-61.
11. Montanaro, U., Wroblewski, M., Dixit, S., Creighton, S., Pragalathan, S. and Sorniotti, A., 2020. Linearising Longitudinal Vehicle Dynamics through Adaptive Control Techniques for Platooning Applications. *International Journal of Powertrains*.
12. Newell, G.F., 2002. A simplified car-following theory: a lower order model. *Transportation Research Part B: Methodological*, *36*(3), pp.195-205.
13. Androulakis, I.P. and Floudas, C.A., 1999. Distributed branch and bound algorithms for global optimization. In *Parallel processing of discrete problems* (pp. 1-35). Springer, New York, NY.
14. Ferreau, H.J., Kirches, C., Potschka, A., Bock, H.G. and Diehl, M., 2014. qpOASES: A parametric active-set algorithm for quadratic programming. *Mathematical Programming Computation*, *6*(4), pp.327-363.
15. Ahn, K., Rakha, H., Trani, A. and Van Aerde, M., 2002. Estimating vehicle fuel consumption and emissions based on instantaneous speed and acceleration levels. *Journal of transportation engineering*, *128*(2), pp.182-190.