

# Energy-aware Trajectory Optimization of Connected and Automated Vehicle Platoons through a Signalized Intersection

A Research Report from the University of California Institute of Transportation Studies

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<b>16. Abstract</b> Traffic signals, while serving an important function to coordinate vehicle movements through intersections, also cause frequent stops and delays, particularly when they are not properly timed. Such stops and delays contribute to significant amount of fuel consumption and greenhouse gas emissions. The recent development of connected and automated vehicle (CAV) technology provides new opportunities to enable better control of vehicles and intersections, that in turn reduces fuel consumption and emissions. In this paper, we propose platoon-trajectory-optimization (PTO) to minimize the total fuel consumption of a CAV platoon through a signalized intersection. In this approach, all CAVs in one platoon are considered as a whole, that is, all other CAVs follow the trajectory of the leading one with a time delay and minimum safety gap, which is enabled by vehicle to vehicle communication. Moreover, the leading CAV in the platoon learns of the signal timing plan just after it enters the approach segment through vehicle to infrastructure communication. We compare our PTO control with the other two controls, in which the leading vehicle adopts the optimal trajectory (LTO) or drive with maximum speed (AT), respectively, and the other vehicles follow the leading vehicle with a simplified Gipps' car-following model. Furthermore, we extend the controls into multiple platoons by considering the interactions between the two platoons. The numerical results demonstrate that PTO has better performance than LTO and AT, particularly when CAVs have enough space and travel time to smooth their trajectories. The reduction of travel time and fuel consumption can be as high as 40% and 30% on average, respectively, in the studied cases, which shows the great potential of CAV technology in reducing congestion and negative environmental impact of automobile transportation.			
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# Energy-aware Trajectory Optimization of Connected and Automated Vehicle Platoons through a Signalized Intersection

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UNIVERSITY OF CALIFORNIA INSTITUTE OF TRANSPORTATION STUDIES

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# Energy-aware Trajectory Optimization of CAV Platoons through a Signalized Intersection

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Traffic signals, while serving an important function to coordinate vehicle movements through intersections, also cause frequent stops and delays, particularly when they are not properly timed. Such stops and delays contribute to significant amount of fuel consumption and greenhouse gas emissions. The recent development of connected and automated vehicle (CAV) technology provides new opportunities to enable better control of vehicles and intersections, that in turn reduces fuel consumption and emissions. In this paper, we propose platoon-trajectory-optimization (PTO) to minimize the total fuel consumption of a CAV platoon through a signalized intersection. In this approach, all CAVs in one platoon are considered as a whole, that is, all other CAVs follow the trajectory of the leading one with a time delay and minimum safety gap, which is enabled by vehicle to vehicle communication. Moreover, the leading CAV in the platoon learns of the signal timing plan just after it enters the approach segment through vehicle to infrastructure communication. We compare our PTO control with the other two controls, in which the leading vehicle adopts the optimal trajectory (LTO) or drive with maximum speed (AT), respectively, and the other vehicles follow the leading vehicle with a simplified Gipps' car-following model. Furthermore, we extend the controls into multiple platoons by considering the interactions between the two platoons. The numerical results demonstrate that PTO has better performance than LTO and AT, particularly when CAVs have enough space and travel time to smooth their trajectories. The reduction of travel time and fuel consumption can be as high as 40% and 30% on average, respectively, in the studied cases, which shows the great potential of CAV technology in reducing congestion and negative environmental impact of automobile transportation.

*Keywords:* Connected-automated vehicle, platoon, fuel consumption, optimal control

## 1. Introduction

Transportation is a major consumer of non-renewable energy. In 2018, the U.S. transportation sector alone consumed over 143 billion gallons of motor fuel, and it is predicted

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11 that the fuel consumption in transportation in the U.S. will remain at a high level in the  
12 foreseeable future [1]. Furthermore, the world consumption of transportation fuel is forecast  
13 to increase significantly with a steady increase in vehicle ownership as incomes in developing  
14 countries rise [2]. There has been a practice of the so-called eco-driving among environmen-  
15 tally conscious drivers, which tries to avoid hard accelerations and decelerations based on  
16 real-time driving conditions, particularly on urban streets with numerous traffic lights [3–  
17 5]. This practice was shown to reduce personal fuel consumption, but without the advance  
18 knowledge of traffic signal status, the practice is based on ad hoc rules and furthermore, its  
19 impact on other drivers, and hence at a system level, is not certain. Fortunately, the rapidly  
20 evolving connected and autonomous vehicle (CAV) technology can overcome these limita-  
21 tions of eco-driving through better communication and greater vehicle control, and hence  
22 provides a powerful tool to reduce both fuel consumption and greenhouse gas emissions more  
23 effectively [6–8].

24 In the transportation system, intersections play a crucial role in assigning and controlling  
25 traffic flow. In many cases, traffic streams on arterial roads are controlled by traffic signals at  
26 intersections. Vehicles must stop at signals on red, which increases their fuel consumption,  
27 emission levels and travel time due to acceleration/deceleration maneuvers and idling re-  
28 quired at traffic signals. In this paper, we propose a platoon-trajectory-optimization (PTO)  
29 method, to control CAVs moving through a signalized intersection as so to minimize the  
30 total fuel consumption of the platoon. In this method, we assume the CAV platoon knows  
31 the traffic light’s schedule before entering the approach of the intersection, and consider all  
32 CAVs in one platoon as a whole, and classify the scenarios of CAVs passing a signalized  
33 intersection into two categories according to whether all CAVs can cross the intersection  
34 within one signal cycle or not, i.e., all CAVs passing the intersection within one green light  
35 window (Scenario I) and the CAVs passing the intersection in two successive green light  
36 windows (Scenario II). In Scenario I, the trajectory of the leading CAVs is copied by the  
37 other ones in the platoon with reaction time delay and a safety space gap, enabled by vehicle  
38 to vehicle communication. In Scenario II, the platoon must be split into two subplatoons,  
39 and the other CAVs in each subplatoon follow the leading one with trajectory copying.

40 In addition, we compare PTO with other two methods based on a simplified Gipps’ car-  
41 following model, i.e., leading-trajectory-optimization (LTO) and aggressive driving (AT). In  
42 LTO method, we suppose the leading vehicle is a CAV, and the others are human-driven  
43 vehicles. The strategy of the leading CAV is to minimize its fuel consumption with optimal  
44 control and pass the signalized intersection without considering the following vehicles. The  
45 human-driven vehicles travel across the intersection with a simplified Gipps’ car-following  
46 model and stop before the intersection when the red light is on. In AT method, we suppose  
47 all vehicles in one platoon are human-driven. The leading vehicle travels with maximum  
48 speed and stops before the intersection until the green light is on. As similar as LTO, the  
49 other vehicles follow the leading vehicle with a simplified Gipps’ car-following model in AT.  
50 Furthermore, we apply the PTO method to control multiple platoons across a signalized  
51 intersection in consideration of the intersections between two platoons. A virtual trajectory  
52 generated based on the last CAV of the platoon in front is taken as a constraint of the back  
53 platoon to ensure safety. The results of case studies and sensitivity analysis demonstrate

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54 PTO outperforms LTO and AT in reducing both fuel consumption and travel time when  
55 the CAVs have enough space and traffic throughput to smooth their trajectories.

56 The rest of this paper is organized as follows. Section 2 reviews related literature. Section  
57 3 presents the results of optimizing one vehicle with optimal control. In Section 4, the  
58 frameworks of PTO and the other two methods, LTO and AT, are described. Case studies  
59 and sensitivity analysis are conducted to compare the performance of the three methods.  
60 In Section 5, we extend the three methods into multiple platoons. As similar as Section  
61 4, we conduct case studies and sensitivity analysis in the multiple-platoon level. Section 6  
62 concludes the paper and discusses some further research directions.

## 63 2. Literature review

64 With the emergence of technologies, such as connected vehicle (CV), autonomous vehicle  
65 (AV) and connected autonomous vehicle (CAV), vehicle trajectory control strategies have  
66 been proposed to reduce fuel consumption for arterial roads controlled by speed limits or  
67 traffic signals in recent years [9–17]. Liu et al. present a fuel-consumption-aware variable-  
68 speed limit (FC-VSL) traffic control scheme to minimize the fuel consumption on freeways  
69 with the problem formulated as an optimal control problem [10]. He et al. propose a multi-  
70 stage optimal control formulation to optimize vehicle trajectory on signalized arterial roads  
71 that considers both vehicle queue and traffic light status [11]. Ubiergo and Jin present a hi-  
72 erarchical green driving strategy based on feedback control to smooth stop-and-go traffic in  
73 signalized networks with vehicle-to-infrastructure (V2I) communication [12]. With numeri-  
74 cal analysis, they demonstrate that their method can save about 15% in travel delays and  
75 8% in fuel consumption and greenhouse gas emissions. Zhou et al. and Ma et al. propose  
76 a parsimonious shooting heuristic algorithm to construct vehicle trajectories on a signalized  
77 highway segment, in which the trajectories of each vehicle is broken into a few sections that  
78 each one is analytically solvable [13, 14]. Li and Zhou propose an intersection automation  
79 policy (IAP) to capture complex traffic dynamics and schedule resources (green lights) to  
80 serve both CAV and human-driven vehicles [15]. Yao et al. present a trajectory smoothing  
81 method based on individual variable speed limits with location optimization (IVSL-LC),  
82 and compare the method with the individual advisory speed limits (IASL). They demon-  
83 strate IVSL-LC method can greatly increase traffic efficiency and reduce fuel consumption  
84 in contrast to IASL [16]. Feng et al. propose a two-stage optimization framework that  
85 combines trajectory smoothing and traffic signal control [17]. Simulation results show that  
86 the framework can reduce 24% vehicle delay and 13.8% CO2 emissions.

87 The above studies mainly focus on solving the problem of trajectory smoothing across  
88 a signalized intersection at the individual vehicle-level. Moreover, with the development of  
89 CAV, it is possible to reduce fuel consumption and travel time at the platoon-level [18–20].  
90 Wei et al. present a set of integer programming and dynamic programming models for  
91 scheduling longitudinal trajectories based on a space-time lattice [18]. By adjusting the lead  
92 vehicle’s speed and platoon-level reaction time at each time step, their framework can control  
93 the complete set of trajectories in a platoon efficiently [18]. Lioris et al. assess the potential  
94 mobility benefits of platooning with connected vehicle technology (CVT), and platooning

95 in CVT environment can double throughput in urban roads [19]. Stebbins et al. propose  
 96 a trajectory optimization method by optimizing for the delay over the entire trajectory  
 97 instead of suggesting an individual speed [20]. Moreover, they extend the framework to  
 98 platoon-level, in which other vehicles follow the leading vehicle with a car-following model.

99 In this paper, we develop a vehicle trajectory control framework for CAV platoons to re-  
 100 duce fuel consumption and travel delay. To take advantage of vehicle to infrastructure (V2I)  
 101 and vehicle to vehicle (V2V) communication in a CAV traffic environment, traffic signal  
 102 timing status is transmitted to the leading CAV vehicle before it enters the intersection, and  
 103 the platoon leaves the intersection at free-flow speed (or the speed limit of the road), which  
 104 serves at the final state condition for our formulated optimal trajectory control problem.  
 105 Our approach first develops the optimal control policy for a single CAV, then extends it to  
 106 a vehicle platoon, and finally designs a mechanism to control multiple platoons traversing a  
 107 signalized intersection considering the interactions between platoons.

### 108 3. Optimal control of one CAV

109 First, let us optimize the trajectory of one CAV with optimal control from location  
 110  $s_0$  to location  $s_1$  ( $s_1 > s_0$ ) without traffic signal. Suppose, at time  $t_0$ , one CAV with  
 111 maximum speed  $v_0$  travel at location  $s_0$ , and the vehicle must arrive at location  $s_1$  at the  
 112 maximum speed of  $v_0$ . In this situation, we need to optimize one trajectory to minimize fuel  
 113 consumption for the vehicle traveling from location  $s_0$  to location  $s_1$  with speed limit. The  
 114 framework for solving this problem can be presented as follows.

115 (1) System Model: For a single vehicle, state vector  $x(t)$  is defined as,

$$\mathbf{x}(t) \triangleq [x_1(t) \ x_2(t)]^T = [s(t) \ v(t)]^T, \quad (1)$$

116 where  $s(t)$  is the distance from  $s_0$ , and  $v(t)$  is the speed of the vehicle. Those two variables  
 117 denote the state of the vehicle. The control vector only contains one variable, i.e., the  
 118 acceleration rate, which is defined as,

$$\mathbf{u}(t) \triangleq [a(t)]^T. \quad (2)$$

119 Therefore, the dynamics of the system can be described with differential equations,

$$\dot{\mathbf{x}}(t) \triangleq \begin{bmatrix} \dot{x}_1(t) = v(t) \\ \dot{x}_2(t) = a(t) \end{bmatrix} \quad (3)$$

120 (2) Optimal Control Problem Formulation: The problem of controlling the CAV is formu-  
 121 lated to minimize the fuel consumption as follows,

$$\mathbf{J} = \int_{t_0}^{t_f} c(v(t), a(t)) dt, \quad (4)$$

122 where  $t_0$  and  $t_f$  are the corresponding time points of  $s_0$  and  $s_1$ , respectively;  $c(v(t), a(t))$  is an  
 123 instantaneous fuel consumption model presented at the Conference of Australian Institutes

124 of Transportation Research (CAITR) [10, 21], which is given by,

$$c(v(t), a(t)) = \begin{cases} \alpha, & a(t) \leq -\frac{R_a(t)+R_r(t)}{M_v} \\ \alpha + \beta_1 R_T(t)v(t), & a(t) \in (-\frac{R_a(t)+R_r(t)}{M_v}, 0) \\ \alpha + \beta_1 R_T(t)v(t) + \frac{\beta_2 M_v a(t)^2 v(t)}{1000}, & a(t) \geq 0 \end{cases} \quad (5)$$

125 where  $R_T(t)$ ,  $R_a(t)$ , and  $R_r(t)$  are the tractive force, air drag, and rolling resistance, respec-  
126 tively. They can be calculated as follows:

$$R_T(t) = M_v a(t) + R_a(t) + R_r(t) + R_g(t) \quad (6)$$

$$R_a(t) = \frac{\rho}{2} C_D A_f v(t)^2 \quad (7)$$

$$R_r(t) = 0.01 \frac{1 + v(t)}{44.73} M_v g \quad (8)$$

129 The definitions and values of the parameters from Eq. 5 to Eq. 8 are shown in Table 1.  
130 Note that the default values of the parameters of the fuel consumption model assume the  
131 vehicle travels in on a flat surface (i.e., grade force  $R_g(t) = 0$ ) and neglect the wind pressure.  
132 However, the fuel consumption model can easily be extended to more general scenarios that  
133 can reflect a real environment by adjusting the values of the parameters of  $R_T$ . Here, for  
the sake of simplification, we only consider the parameters shown in Table 1.

Table 1: Parameter definitions and values in the fuel consumption model.

Parameter	Definition	Value
$\alpha$	Idle fuel consumption rate	0.375mL/s
$\beta_1$	Efficiency parameter	0.09mL/kJ
$\beta_2$	Energy-acceleration efficiency parameter	0.03mL/(kJ.m/s <sup>2</sup> )
$M_v$	Average vehicle mass	1400kg
$\rho$	Air density	1.2256kg/m <sup>3</sup>
$C_D$	Drag coefficient	0.54
$A_f$	Average vehicle frontal area	2.1m <sup>2</sup>
$g$	Standard gravity	9.8m/s <sup>2</sup>

134 The above optimal control problem is challenging to find analytical solutions [10]. In-  
135 stead, the numerical Gauss pseudospectral method (GPM) is used to discretize a continuous  
136 optimal control problem into a nonlinear program (NLP) and obtain the optimal solution.  
137 The technique is an orthogonal collocation method where the collocation points are the  
138 Legendre-Gauss (LG) points [22]. Here, we employ the General Algebraic Modeling System  
139 (GAMS) to obtain the optimal control solution [23].

140 Figure 1 presents the optimal results with different travel distance, maximum speed,  
141 deceleration/acceleration constraint, and LG points. Figure 1(a)-(d) show the relationship  
142 between optimal fuel consumption and travel time. The corresponding travel time with  
143

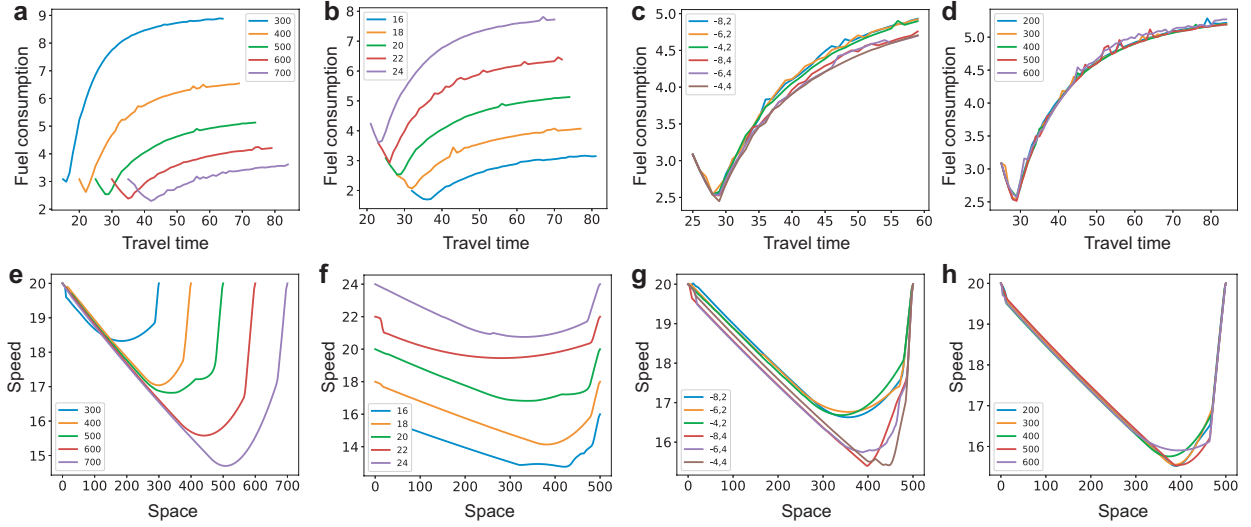


Figure 1: Optimal control outcomes of one CAV. (a-d) The relationship between optimal fuel consumption per 100 meters and travel time; (e-h) The relationship between travel speed and space for optimal trajectories with lowest fuel consumption. (a, e) Optimal results with different control space  $s_1$  and the same maximum speed ( $v_0 = 20m/s$ ) and deceleration/acceleration constraint ( $a_{br} = -4m/s^2, a_{fw} = 2m/s^2$ ) and number of LG points ( $N_{LG} = 200$ ). (b, f) Optimal results with different maximum speed and the same control space ( $s_1 = 500m$ ) and deceleration/acceleration constraint ( $a_{br} = -4m/s^2, a_{fw} = 2m/s^2$ ) and number of LG points ( $N_{LG} = 200$ ). (c, g) Optimal results with different deceleration/acceleration constraint and the same control space ( $s_1 = 500m$ ), maximum speed ( $v_0 = 20m/s$ ) and number of LG points ( $N_{LG} = 200$ ). (d, h) Optimal results with different number of LG points and the same control space ( $s_1 = 500m$ ) and maximum speed ( $v_0 = 20m/s$ ) and deceleration/acceleration constraint ( $a_{br} = -4m/s^2, a_{fw} = 2m/s^2$ ).

144 the lowest fuel consumption is a little longer than the shortest travel time with constant  
145 maximum speed. At a given travel distance, the optimal fuel consumption decreases firstly  
146 and then increases over travel time. Figure 1(e)-(h) show the optimal trajectories with lowest  
147 fuel consumption. The CAV traveling with lowest fuel consumption needs to decelerate  
148 firstly, and then gradually accelerate to maximum speed. It is a bit counterintuitive at  
149 first because it is generally believed that keeping a constant velocity would consume less  
150 fuel in contrast to a trajectory with speed variations. However, a closer examination of the  
151 fuel consumption model of Eq. 5 reveals the reason for this counterintuitive phenomenon.  
152 When the acceleration  $a \geq 0$ , even though it has a high impact on the fuel consumption  
153 in the third term, vehicle speed  $v(t)$  dominates in both the second and third terms. The  
154 implication is that the effects of the lower speed could offset the impact of high acceleration  
155 rate on fuel consumption. Besides, we find the deceleration/acceleration constraint and the  
156 number of LG points do not have a significant influence on the performance of optimal  
157 control. Therefore, in the following sections, we set the maximum brake deceleration as  
158  $a_{br} = -4m/s^2$ , maximum acceleration as  $a_{fw} = 2m/s^2$  and the number of LG points as  
159  $N_{LG} = 200$ .

---

## 160 4. Platoon optimization

### 161 4.1. The framework of PTO method

162 Based on the optimal control framework for one vehicle described in the above section,  
163 we propose the PTO method to optimize one platoon across a signalized intersection by  
164 considering all CAVs in the platoon as a whole. The components of the PTO method are  
165 described as follows.

166 **Road:** We only consider one single lane leading to a signalized intersection. The leading  
167 CAV in one platoon enters location  $s_0$  and arrives location  $s_1$  with maximum speed  $v_0$ . The  
168 traffic signal is installed at location  $s_1$ .

169 **Traffic Signal:** The traffic signal we consider here is a fixed signal timing including a  
170 sufficient length of  $G$  and an effective red time of  $R$ . Thus, the cycle length of the traffic  
171 signal is  $C := G + R$ .

172 **Platoon:** The number of CAVs in one platoon is  $N$ . The initial state of the platoon (the  
173 leading CAV) arriving at location  $s_0$  is that all CAVs have the same speed of  $v_0$  and the space  
174 between two vehicles in the platoon is same. Suppose the reaction time of CAV is  $\tau$  and the  
175 minimum gap between the two vehicles is  $d$ . The space between two CAVs at initial state  
176 is  $l = d + v_0\tau$ , and the total length of the platoon at initial state is  $L_p = (d + v_0\tau)(N - 1)$ .  
177 Moreover, we suppose all CAVs in one platoon can pass the green light windows if the leading  
178 vehicle arrives the intersection at the beginning of the green light window, i.e.,  $G > \frac{(N-1)l}{v_0}$ .

179 **Trajectory copying:** The basic idea of PTO method is that all vehicles can copy the  
180 trajectory of the leading vehicles with reaction time delay and minimum gap delay. Figure 2  
181 presents an illustration of trajectory copying, in which Trajectory 1 is the trajectory of the  
182 leading CAV in one platoon, and the following CAV in the platoon can copy Trajectory 1  
183 with time delay  $\tau$  and minimum gap delay  $d$ , and travel along Trajectory 2.

184 **Two scenarios:** For one platoon across a signalized intersection, we divide the process into  
185 two scenarios according to whether the platoon can pass the signalized intersection in one  
186 green light window. The two scenarios are described as follows.

- 187 • Scenario I: The platoon can pass the signalized intersection within one green light  
188 window.
- 189 • Scenario II: The CAVs in one platoon cannot pass the intersection within a green light  
190 window. The platoon must be split into two sub platoons, i.e., Subplatoon A (the  
191 former one) and Subplatoon B (the latter one), and pass the signalized intersection in  
192 two successive green light windows.

193 Figure 3 illustrates the operations of controlling one platoon across a signalized inter-  
194 section with PTO. The platoon is composed of 6 CAVs, which can not pass the intersection  
195 within one green light window (Scenario II). The platoon is split into two sub platoons, and  
196 3 CAVs in each subplatoon. As shown in Figure 3, the control space of Subplatoon A (blue  
197 trajectories) and Subplatoon B (black trajectories) are  $s_1 - s_0$  and  $s_1 - s_0 + 3(v_0\tau + d)$ ,  
198 respectively.

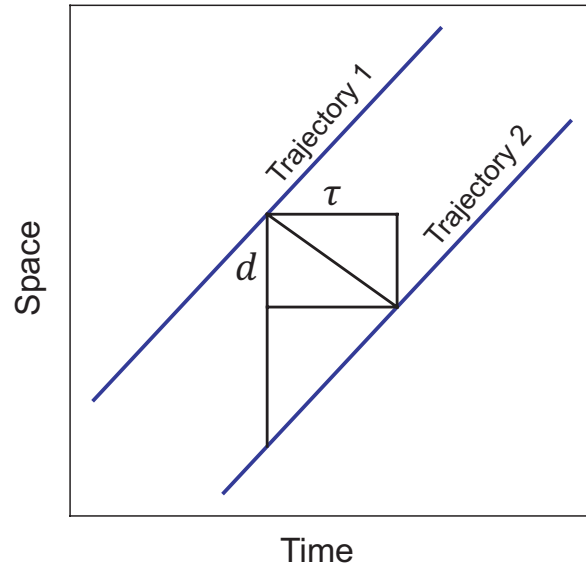


Figure 2: Illustration of trajectory copying.

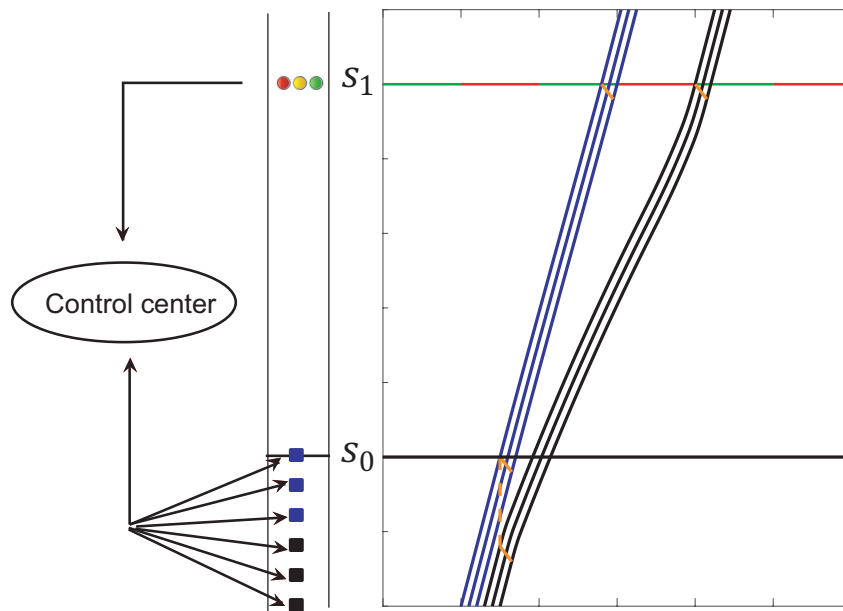


Figure 3: Illustration of control framework of PTO method.



199 Taking Scenario I and Scenario II into consideration, the total fuel consumption of one  
 200 platoon with PTO method across a signalized intersection can be formulated as,

$$J_p = N_A J_A + N_B J_B, \quad (9)$$

201 where  $N_A \geq 0$  and  $N_B \geq 0$ ;  $N_A$  ( $N_B$ ) denotes the number of CAVs and  $J_A$  ( $J_B$ ) the fuel  
 202 consumption of one vehicle in Subplatoon A (B). Substituting  $J_A$  and  $J_B$  with Eq. 4, we  
 203 can obtain,

$$J_p = N_A \left[ \int_{t_0}^{t_f^A} c(v(t), a(t)) dt + c(v_0, 0) L_p / v_0 \right] + N_B \left[ \int_{t_0}^{t_f^B} c(v(t), a(t)) dt + c(v_0, 0) (L_p - (v_0 \tau + d) N_A / v_0) \right], \quad (10)$$

204 where  $t_0$  is the starting time of optimizing the leading CAV in Subplatoon A (B);  $t_f^A$  and  
 205  $t_f^B$  are the ending time of optimizing leading CAV in Subplatoon A and Subplatoon B,  
 206 respectively. Unlike the optimal control of one CAV, the length of the platoon is considered  
 207 in the control framework of one platoon. The locations of leading CAVs in Subplatoon A  
 208 and Subplatoon B at  $t_0$  are  $s_0$  and  $s_0 - N_A(v_0 \tau + d)$ , respectively. The locations of leading  
 209 CAVs in the two sub platoons at  $t_f^A$  and  $t_f^B$  are both  $s_1$ .

210 The platoon optimization of passing a signalized intersection is to minimize  $J_p$  with all  
 211 CAVs traveling across the intersection in green light windows. The constraints of guar-  
 212 anteeing all vehicles crossing the intersection within green light windows can be described  
 213 as,

$$\begin{cases} t_f^A \setminus C \leq G \\ (t_f^A + (N_A - 1)(\tau + d/v_0)) \setminus C \leq G \\ \lfloor t_f^A \rfloor = \lfloor t_f^A + (N_A - 1)(\tau + d/v_0) \rfloor \\ t_f^B \setminus C \leq G \\ (t_f^B + (N_B - 1)(\tau + d/v_0)) \setminus C \leq G \\ \lfloor t_f^B \rfloor = \lfloor t_f^B + (N_B - 1)(\tau + d/v_0) \rfloor \\ \lfloor t_f^A \rfloor + 1 = \lfloor t_f^B \rfloor \end{cases} \quad (11)$$

214 The first six equations in Eq. 11 can guarantee all CAVs in Subplatoon A (B) across one  
 215 green light window, and the last equation can ensure Subplatoon A and Subplatoon B get  
 216 through the intersection at two successive traffic signal cycles.

217 In combination of constraint conditions of Eq. 11 and fuel consumption of Eq. 5, we can  
 218 obtain the optimization trajectories of all vehicles in one platoon with minimizing the total  
 219 fuel consumption described in Eq. 10.

#### 220 4.2. Two other methods for comparison

221 We compare our trajectory optimization framework PTO with two other methods that  
 222 adopt a simplified Gipps' car-following model, namely leading-trajectory-optimization (L-  
 223 TO) and aggressive-trajectory (AT). In the LTO method, we assume the leading vehicle in  
 224 a platoon is a CAV, and optimize its trajectory based on the optimal control framework.  
 225 The other vehicles in the platoon are human-driven ones and follow the leading vehicle with  
 226 the simplified Gipps' car-following model [12, 24, 25]. If the following vehicles arrive at the

227 signalized intersection in red, they need to stop until the green light is on. For the AT  
 228 method, we assume there is no CAV in the platoon, and the leading vehicle travel from  $s_0$   
 229 to  $s_1$  with maximum speed  $v_0$ . If the leading vehicle arrives at the intersection in red, it  
 230 is forced to wait until the green light is on; otherwise, it travels through the intersection  
 231 with maximum speed. The other vehicles in the platoon follow the leading vehicle with the  
 232 simplified Gipps' car-following model and stop if the red light is on.

233 The upper limits of acceleration defined in simplified Gipps' car-following model includes  
 234 two parts, i.e., free-flow and congested traffic acceleration, which is formulated as,

$$\begin{cases} a_i^{\text{free}} = 2.5a_{fw}(1 - \frac{v_i(t)}{v_0})\sqrt{0.025 + \frac{v_i(t)}{v_0}} \\ a_i^{\text{cong}} = \frac{1}{T}[\frac{1}{\tau_c}(s_{i-1}(t) - s_i(t) - d - \frac{v_{i-1}(t)^2 - v_i(t)^2}{2a_{br}}) - v_i(t)] \end{cases} \quad (12)$$

235 where  $T$  is the sensitivity coefficient,  $\tau_c$  the drivers' time of reaction, and  $d$  the minimum  
 236 gap between two adjacent vehicles. The acceleration of vehicle  $i$  at time  $t$  is,

$$a_i(t) = \max\{a_{br}, \min\{a_i^{\text{free}}(t), a_i^{\text{cong}}(t)\}\}. \quad (13)$$

237 The speed and location of one vehicle in the next time step with Gipps' car-following model  
 238 are defined as,

$$\begin{cases} v_i(t + \Delta t) = \max\{0, \min\{v_i(t) + a_i(t)\Delta t, v_0\}\} \\ s_i(t + \Delta t) = \max\{s_i(t), \min\{s_i(t) + v_0\Delta t, s_i(t) + v_i(t)\Delta t + \frac{a_i(t)\Delta t^2}{2}\}\} \end{cases} \quad (14)$$

239 where  $\Delta t$  is the time step between iterations.

### 240 4.3. Case study

241 In this section, we conduct one case study to illustrate the performance of our pro-  
 242 posed platoon optimization method PTO and the other two methods, LTO and AT. The  
 243 parameters in the case study are set as follows: enter location  $s_0 = 0$ , traffic signal location  
 244  $s_1 = 500m$ , maximum speed  $v_0 = 20m/s$ , CAV reaction time  $\tau = 1.5s$ , and driver's reaction  
 245  $\tau_c = 2s$ . The number of vehicles in the platoon is  $N = 6$ , and the length of the platoon is  
 246  $L_p = 200m$  at the initial state. The cycle length of traffic signal is  $C = 40s$ , and  $R = G$ .  
 247 The parameters in the fuel consumption model are shown in Table 1.

248 Figure 4 displays trajectories of all vehicles in one platoon with different entry time  
 249 at location  $s_0$ . The first, second and third row denote the results of PTO, LTO and AT,  
 250 respectively. The first two columns are illustrations of Scenario I, in which all vehicles  
 251 can pass the intersection at one green window. The trajectories in the last column belong  
 252 to Scenario II, in which one platoon needs to split into two subplatoons and passes the  
 253 signalized intersection in two successive green light windows. Table 2 shows the average fuel  
 254 consumption and travel time per vehicle per 100 meters for the platoons shown in Figure 4.  
 255 We calculate the fuel consumption and travel time of each vehicle from location  $s_0 - L_p$  to  
 256 location  $s_1 + (v_0^2)/2a_{fw}$  with considering the length of a platoon and the acceleration space  
 257 of human-driven vehicles to compare the performance of PTO, LTO and AT. When entry

258 time  $t_0 = 5$ , the trajectories with AT are blocked by a red signal and need to wait before  
 259 the intersection until the light is on green, however, the vehicles with PTO and LTO can  
 260 adjust their trajectories to avoid stopping before the signalized intersection. In this case, the  
 261 trajectories with LTO consumes less fuel than PTO and AT because the following vehicles  
 262 with LTO have more space and time to smooth their trajectories than PTO. When entry  
 263 time  $t_0 = 15s$ , all vehicles can pass the signalized intersection without the influence of red  
 264 light, and PTO outperforms LTO and AT in fuel consumption. Because all vehicles with  
 265 AT can travel from  $s_0$  to  $s_1$  and cross the intersection with maximum speed, the travel time  
 266 of AT is lowest among the three methods. When the entry time  $t_0 = 30s$ , the trajectories  
 267 with PTO are optimized in each subplatoon and pass the intersection with maximum speed.  
 268 In this case, the PTO method can reduce both fuel consumption and travel time in contrast  
 269 to the other two methods.

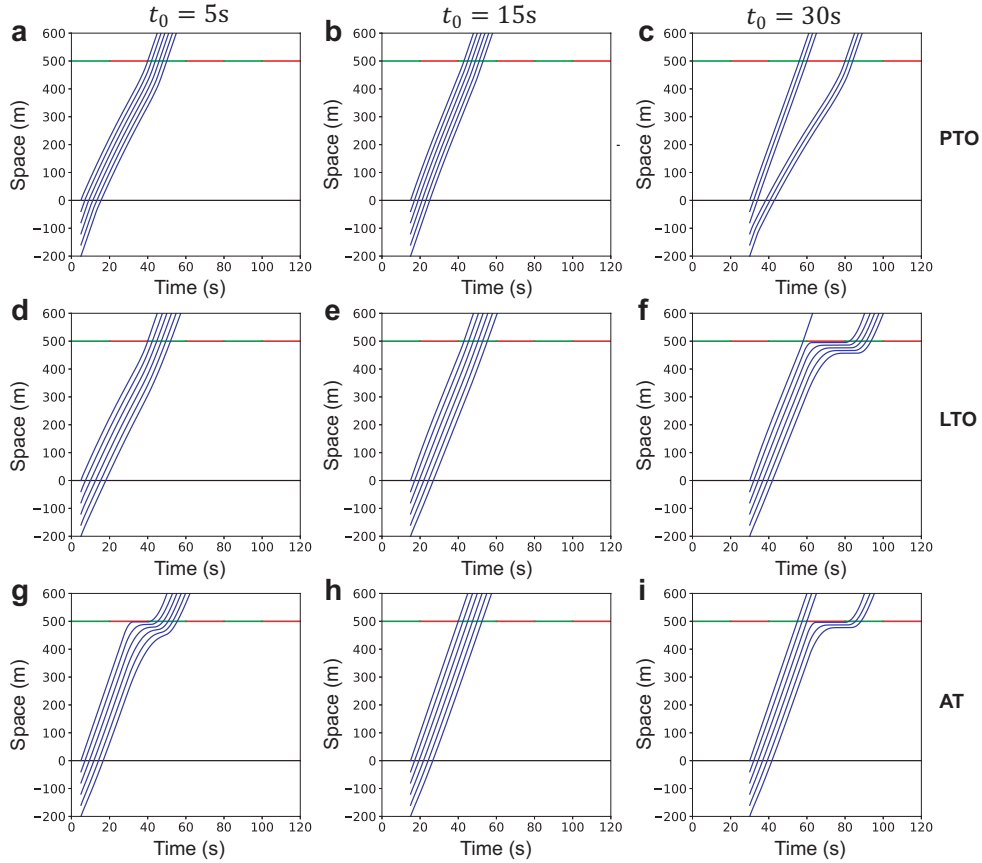


Figure 4: Trajectories of one platoon entering at different times. (a-c) Trajectories with PTO, (d-f) trajectories with LTO and (g-i) trajectories with AT.

270 Figure 5 (a) presents average fuel consumption per vehicle per 100 meters for one platoon  
 271 entering location  $s_0$  at different times  $t_0$ . Overall, the performance of PTO is better than  
 272 LTO and AT in fuel consumption. The mean values of fuel consumption per vehicle per

Table 2: Average fuel consumption and travel time per vehicle per 100 meters shown in Figure 4.

$t_0$	Fuel consumption ( $ml$ )			Travel time ( $s$ )		
	5	15	30	5	15	30
PTO	3.39	2.74	3.15	6.25	5.38	6.25
LTO	3.08	3.12	4.34	6.41	5.53	8.12
AT	5.17	3.54	4.58	7.04	5.16	6.59

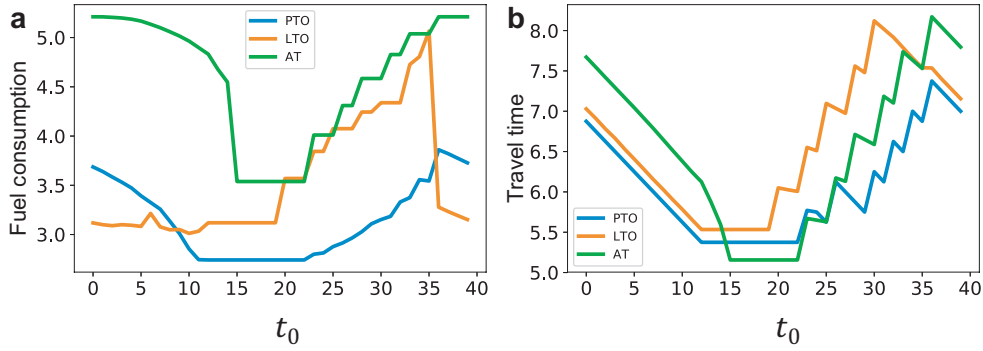


Figure 5: The performance of fuel consumption ( $ml$ ) and travel time ( $s$ ) per vehicle per 100 meters with PTO, LTO and AT methods for different entry time. The parameters are set for simulation:  $s_1 = 500m$ ,  $v_0 = 20m/s$ ,  $N = 6$ , and  $C = 40s$ .

273 100 meters over different entry times in one cycle of traffic signal with PTO, LTO and AT  
274 are 3.14, 3.54 and 4.59  $ml$ , respectively. In contrast to LTO and AT, the fuel consumption  
275 with PTO method falls by about 11.30% and 31.59%, respectively. When all vehicles are  
276 blocked by red light and need to pass the intersection at next traffic signal cycle, the fuel  
277 consumption with LTO may outperform PTO. In this condition, the following vehicles with  
278 a simplified Gipps' car-following model have more space and travel time to smooth their  
279 trajectories. Figure 5 (b) depicts the results of average travel time per vehicle per 100  
280 meters. The mean values of travel time over different entry times in one cycle of traffic  
281 signal with PTO, LTO and AT are 6.06, 6.60 and 6.52 seconds, respectively. Even though  
282 we only take fuel consumption as our optimization objective, the performance of PTO in  
283 reducing travel delay is better than LTO and AT because CAVs have less reaction time and  
284 pass the signalized intersection with maximum speed in PTO method. Compared with LTO  
285 and AT, the travel time reduced about 8.18% and 7.06% in PTO method, respectively. All  
286 in all, from the case study, we find the PTO method can not only reduce fuel consumption  
287 but also ease traffic congestion and increase traffic efficiency.

288 4.4. Sensitivity analysis

289 From the previous case study, we find our PTO method is beneficial for reducing fuel  
 290 consumption and travel delay. In this section, we analyze how the values of the critical  
 291 parameters influence the performance of PTO, LTO and AT methods. Figure 6 presents  
 292 the results of sensitivity analysis about different control space  $s_1$ , maximum speed  $v_0$ , the  
 293 number of vehicles in one platoon  $N$ , and the length of traffic signal cycle  $C$ .

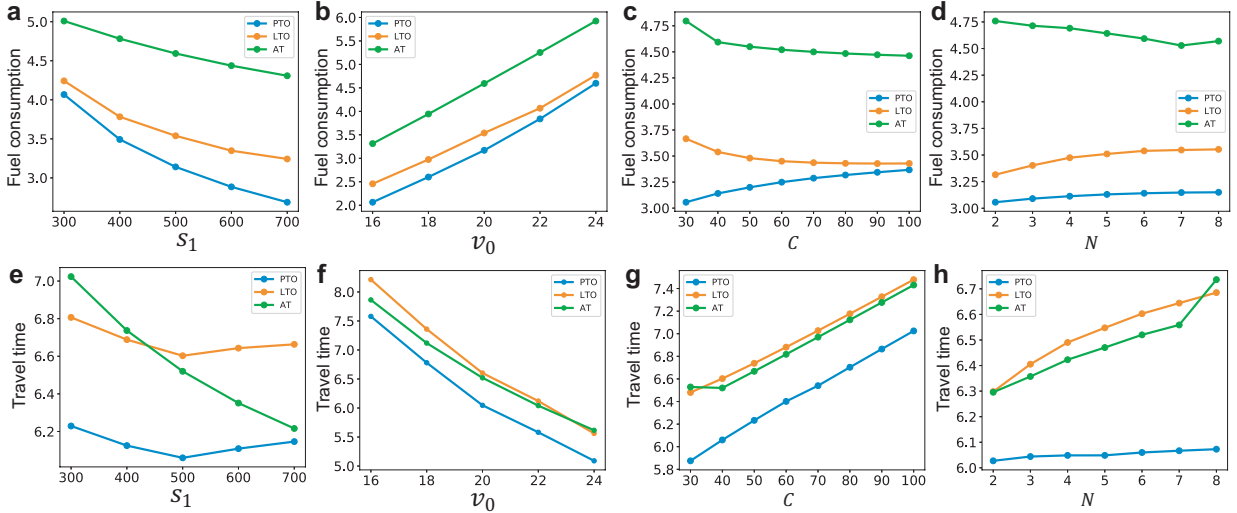


Figure 6: Sensitivity analysis of one platoon across a signalized intersection with different parameters. (a-d) Fuel consumption and (e-h) travel time per vehicle per 100 meters. The parameters except for parameters analyzed are set as:  $s_1 = 500m$ ,  $v_0 = 20m/s$ ,  $N = 6$  and  $C = 40s$ . All data points are calculated over different entry times in one traffic signal cycle.

294 As shown in Figure 6 (a), the average fuel consumption of the three methods all decreases  
 295 with the increase of control space. The gap in fuel consumption between PTO and the  
 296 other two methods also increases with the increase of control space. Figure 6 (b) shows the  
 297 average fuel consumption with different maximum speeds. The average fuel consumption of  
 298 the three methods all increases with the maximum speed, because travel speed contributes  
 299 positively to the second and third terms in the fuel consumption model in Eq. 5. Figure 6 (c)  
 300 shows the sensitivity of the length of the traffic signal cycle on fuel consumption. The fuel  
 301 consumption of the PTO method increases with the increase of the cycle length. However,  
 302 for the other two methods, the fuel consumption decreases with the increase of the length  
 303 of the traffic signal cycle. It is because the fuel consumption with optimal control increases  
 304 with travel time (see Figure 1). When the traffic signal has a significantly long cycle, the  
 305 PTO method, by requiring the CAV platoon to arrive at the start of the green interval,  
 306 does not take full advantage of the the long green time window. Figure 6 (d) shows that  
 307 the fuel consumption increases slightly with large platoon size, and the number of vehicles  
 308 in one platoon does not have a significant influence on the fuel consumption of PTO. Fig-  
 309 ure 6 (e-h) show the results of travel time in different conditions. Even though we only

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310 take fuel consumption as our optimization objective, the PTO method is also beneficial to  
311 reduce travel time compared with LTO and AT methods. In summary, our PTO method  
312 considerably outperforms the LTO method in reducing fuel consumption and increasing  
313 traffic throughput in the situation with longer control distance, lower maximum speed and  
314 shorter traffic signal cycle. Moreover, even though only the leading vehicle is CAV in LTO  
315 method, it can improve the performance in fuel consumption and travel time in comparison  
316 with AT, which is consistent with both theoretical and experimental found in the literature  
317 results [12, 16, 26].

## 318 5. Optimization of multiple platoons

### 319 5.1. The constraint between two platoons

320 The previous results are for one platoon with different entry times, and no interaction  
321 between two platoons is considered. Therefore, in this section, we extend our PTO method  
322 to multiple platoons. The probability of the leading vehicle in platoon  $k$  entering location  
323  $s_0$  at time  $t_{k,1}$  according to the time of the last vehicle in platoon  $k - 1$  entering location  $s_0$   
324 is described as,

$$p(t_{k,1}) = \lambda e^{-\lambda[(t_{k,1} - t_{k-1,N}) - \tau_p]}, \quad (15)$$

325 where  $\lambda$  is the average event rate,  $\tau_p$  is minimum time headway between two platoons, and  
326  $t_{k,1}$  and  $t_{k-1,N}$  denotes the time of the leading vehicle in platoon  $k$  and the last vehicle in  
327 platoon  $k - 1$  entering location  $s_0$ , respectively.

328 For multiple platoons, the behaviors of one platoon will affect the performance of the  
329 next platoon. If we optimize the trajectory of platoon by platoon, the trajectory of the last  
330 vehicle in platoon  $k - 1$  may cross with the trajectory of the leading vehicle in platoon  $k$ . To  
331 avoid a crash between two platoons, we suppose one virtual vehicle follow the last vehicle in  
332 platoon  $k - 1$  with time delay  $\tau$  and space delay  $d$ . The trajectory of the virtual vehicle in  
333 platoon  $k - 1$  is the constraint of the leading vehicle in platoon  $k$ , which can be described  
334 as,

$$s_{k-1}^{\text{virtual}}(t) \geq s_{k,1}(t), \quad (16)$$

335 where  $s_{k-1}^{\text{virtual}}(t)$  and  $s_{k,1}(t)$  denote the locations of virtual vehicle in platoon  $k - 1$  and the  
336 leading vehicle in platoon  $k$  at time  $t$ , respectively. Moreover, the constraint between two  
337 platoons also is applied to avoid a crash between two subplatoons.

### 338 5.2. Case study

339 In this section, a case study is conducted to compare the performance of PTO, LTO and  
340 AT for multiple platoons. The parameters in the case study are set as follows: the number  
341 of platoons  $N_p = 10$ , the average event rate  $\lambda = 0.2$ , and the minimum time difference  
342 between two platoons  $\tau_p = 10s$ . The other parameters are the same as the case mentioned  
343 above for one platoon.

344 Figure 7 illustrates trajectories of multiple platoons. Overall, the PTO method can re-  
345 duce congestion and let more vehicles cross the signalized intersection in less traffic signal

346 cycles in contrast to LTO and AT. According to the trajectories of multiple platoons in Fig-  
 347 ure 7, we can obtain the average fuel consumption and travel time per vehicle per 100 meters  
 348 which are shown in Table 3. We can see that more than 30% of fuel consumption and 40%  
 349 of travel time are reduced with PTO method in contrast to LTO and AT method. However,  
 350 because LTO only has a local influence on multiple platoons across a signalized intersection,  
 351 the fuel consumption of the LTO method is not significantly reduced in comparison with  
 352 AT. In some cases, compared with AT, LTO method may increase traffic congestion.

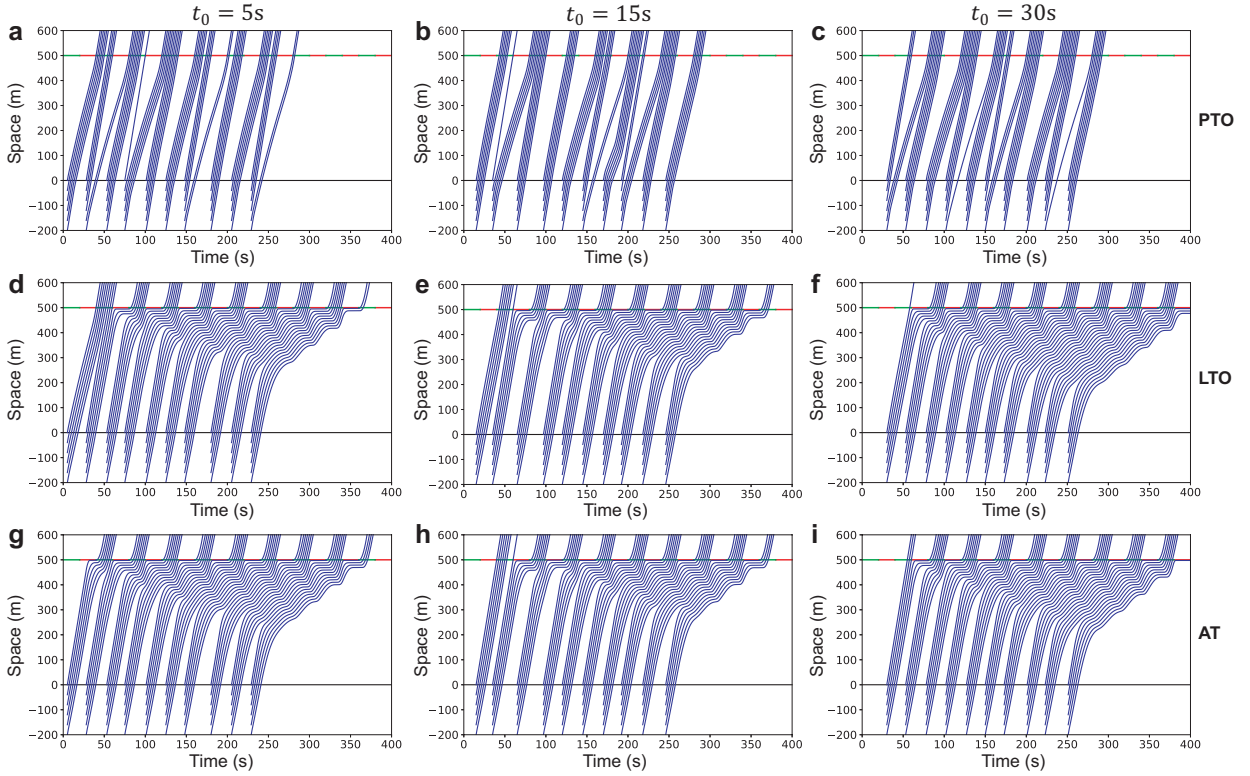


Figure 7: Trajectories of multiple platoons across a signalized intersection. (a-c) Trajectories with PTO, (d-f) trajectories with LTO and (g-i) trajectories with AT.

Table 3: Average fuel consumption and travel time per vehicle per 100 meters shown in Figure 7.

$t_0$	Fuel consumption ( $ml$ )			Travel time ( $s$ )		
	5	15	30	5	15	30
PTO	3.21	3.35	3.38	5.73	5.72	5.84
LTO	4.84	4.89	4.92	11.06	10.48	13.72
AT	5.00	4.89	4.95	12.43	10.44	12.23

353 Figure 8 shows the cumulative distribution function (CDF) of fuel consumption and  
 354 travel time. In Figure 8 (a), the mean values of fuel consumption are 3.32, 4.94 and 4.99 *ml*  
 355 per vehicle per 100 meters with PTO, LTO and AT, respectively. In contrast to LTO and  
 356 AT, the fuel consumption with PTO method falls by about 32.79% and 33.47%, respectively.  
 357 It is clear that the fuel consumption of most vehicles is less than 4 *ml* with the PTO method.  
 358 However, the fuel consumption of most vehicles with LTO and AT is more than 4 *ml*. In  
 359 Figure 8 (b), the mean values of travel time are 5.73, 10.97 and 11.10 seconds with PTO,  
 360 LTO and AT, respectively. In comparison with LTO and AT, the travel time with PTO  
 361 method decreases about 47.8% and 48.4%, respectively. The travel time of most vehicles is  
 362 less than 8 seconds with PTO; however, the cumulative probabilities of travel time with LTO  
 363 and AT are gradually increasing with travel time, indicating PTO method can effectively  
 364 reduce traffic congestion.

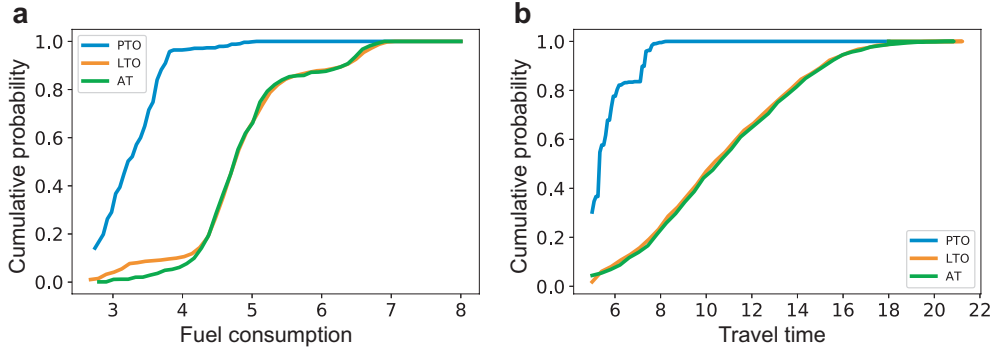


Figure 8: Cumulative probability of fuel consumption (*ml*) and travel time (*s*). The data is generated by 50 independent simulations.

### 365 5.3. sensitivity analysis

366 From the above case study, we find our PTO method can reduce more than 30% fuel  
 367 consumption and 40% travel time than the other two methods. In this section, we analyze the  
 368 influence of key parameters on the performance of PTO, LTO and AT methods. Figure 9  
 369 and Figure 10 show the fuel consumption and travel time with different parameters. As  
 370 shown in Figure 9, some parameters, e.g.,  $v_0$ ,  $C$ ,  $N$  and  $\lambda$ , have negative impacts on the fuel  
 371 consumption of PTO for multiple platoons. As similar as one platoon, in those parameters,  
 372 it is obvious that the increase of  $v_0$  and  $C$  will contribute more to the fuel consumption.  
 373 As shown in Figure 9 (c), when the length of traffic signal  $C$  is large enough, The unit  
 374 fuel consumption of PTO method gradually approaches those of the other two methods,  
 375 which indicate that our PTO method is better suited for short and moderately long cycles  
 376 (less than 90 seconds). Moreover, in Figure 9 (d) and (f), more vehicles in one platoon and  
 377 higher arrival rate of platoons cause the increase of the density of vehicles, leading more  
 378 fuel consumption. Combing the results in Figure 9 and Figure 10, we find the increase of  
 379 the length of traffic signal cycle and the density of vehicles go against the performance of



380 PTO in both fuel consumption and traffic throughput. In general, the PTO method can  
 381 significantly improve the performance of fuel consumption and traffic throughput in contrast  
 382 to LTO and AT when vehicles have enough space to smooth their trajectories. However, for  
 383 multiple platoons, the performance of LTO cannot be significantly improved in comparison  
 384 with AT in most cases because the impact of CAV would be non-existent or substantially  
 385 lessened [27].

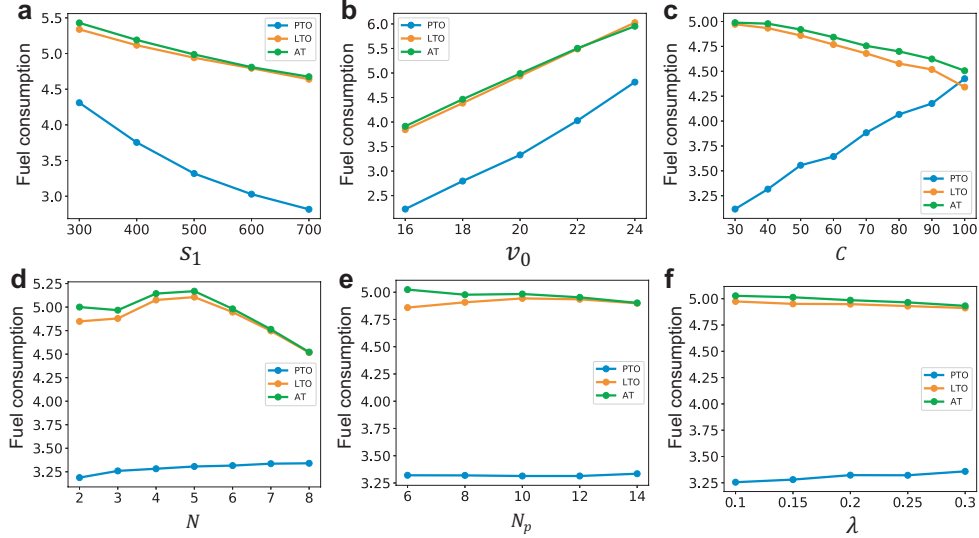


Figure 9: Fuel consumption ( $ml$ ) per vehicle per 100 meters for multiple platoons across a signalized intersection. The parameters except for parameters analyzed are set as:  $s_1 = 500m$ ,  $v_0 = 20m/s$ ,  $N = 6$ ,  $C = 40s$ ,  $N_p = 10$ ,  $\lambda = 0.2$  and  $\tau_p = 10s$ . All data points are calculated over 50 independent simulations.

## 386 6. Conclusions and Discussions

387 In this paper, we propose a platoon-based trajectory optimization method, i.e., PTO,  
 388 to reduce fuel consumption of vehicles passing through a signalized intersection. In the  
 389 PTO method, all vehicles are CAVs, and the CAVs in one platoon follow the leading one  
 390 with a reaction time delay and safety space gap. The method can smooth the trajectories  
 391 of vehicles, eliminate full stops, economize fuel consumption, and ease traffic congestion.  
 392 Moreover, we compare the PTO method with the other two methods, LTO and AT. In  
 393 LTO, only the leading vehicle is a CAV with optimized trajectory, and the other vehicles  
 394 follow the leading CAV with Gipps' car-following model. In AT, we simulate the condition  
 395 that all vehicles are human-driven and no optimization is applied.

396 Through a series of case studies and sensitivity analysis, we verify that our PTO method  
 397 has advantages in economizing fuel consumption and reducing travel time over the other  
 398 two methods. We find there are negative relationships between fuel consumption and the  
 399 length of the traffic signal cycle, maximum speed, the density of vehicles. Because when  
 400 those factors have large values, it is equivalent to reducing the space used for trajectory

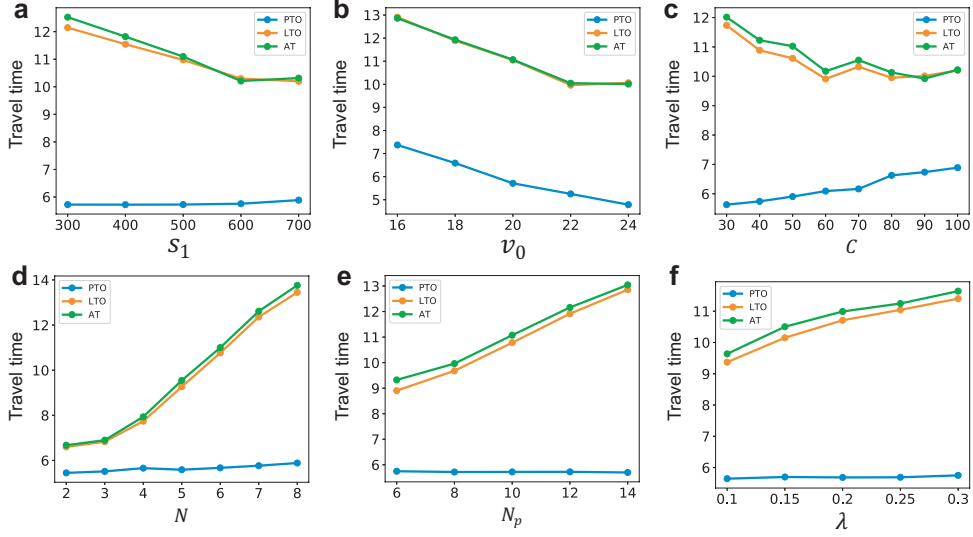


Figure 10: Travel time ( $s$ ) per vehicle per 100 meters for multiple platoons across a signalized intersection. The parameters except for parameters analyzed are set as:  $s_1 = 500m$ ,  $v_0 = 20m/s$ ,  $N = 6$ ,  $C = 40s$ ,  $N_p = 10$ ,  $\lambda = 0.2$  and  $\tau_p = 10s$ . All data points are calculated over 50 independent simulations.

Table 4: Average fuel consumption and travel time per vehicle per 100 meters shown in Figure 11.

$t_0$	Fuel consumption ( $ml$ )			Travel time ( $s$ )		
	5	15	30	5	15	30
PTO	3.16	3.25	3.27	5.48	5.44	5.52
LTO	4.77	4.77	4.85	9.14	8.74	10.77
AT	4.90	4.76	4.84	9.99	8.71	9.86

401 optimization. From this perspective, the PTO method needs enough space to let all CAVs  
 402 take optimal trajectories. When the traffic is heavy, and there is not enough space for CAVs  
 403 to smooth their trajectories, the performance of the PTO method degrades and approaches  
 404 those of LTO and AT. This indicates that the PTO method is best suited to undersaturated  
 405 traffic conditions with shorter or moderately long cycles.

406 In the above analysis, we only consider multiple platoons across an isolated signalized  
 407 intersection. However, in general, traffic signals are usually coordinated based on a time-  
 408 distance (T-D) diagram so that platoons can pass the intersections along with a “green  
 409 wave” without the influence of red light [28]. Figure 11 illustrates the trajectories of multiple  
 410 platoons across two successive signalized intersections. The offset between the two traffic  
 411 signals is set as  $T_C = (s_2 - s_1)/v_0$ , where  $s_2$  is the location of the second intersection.  
 412 As shown in Figure 11 (a-c), all platoons with the PTO method can travel from the first  
 413 intersection to the second intersection with maximum speed and pass the second intersection

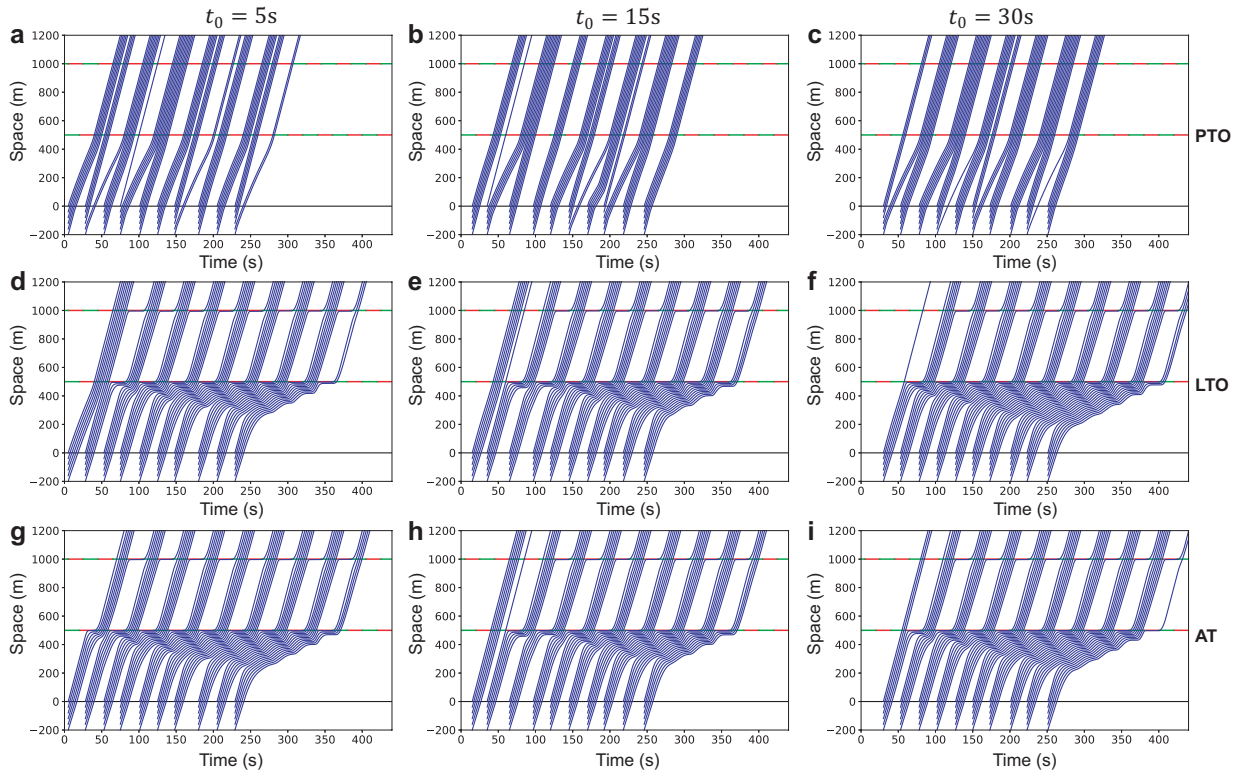


Figure 11: Trajectories of multiple platoons across two signalized intersections. (a-c) Trajectories with PTO, (d-f) trajectories with LTO and (g-i) trajectories with AT.

414 without stopping. In the case of LTO and AT (Figure 11 (d-i)), however, there are some  
 415 vehicles that cannot cross the second intersection along with the “green wave”, and need to  
 416 stop before the second intersection until the light turns green. This highlights the added  
 417 advantage of the PTO method over LTO and AT methods when traffic lights are coordinated.  
 418 The results of average fuel consumption and travel time per vehicle per 100 meters for  
 419 multiple platoons across two intersections in Figure 11 are shown in Table 4.

420 Several research directions can be pursued to extend this research, which includes, but  
 421 is not limited to (1) to develop a PTO method for electric vehicles (EV), (2) to extend the  
 422 PTO method for a network of traffic intersections, and (3) to extend the PTO method with  
 423 actuated control traffic signals.

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