



Connected automated vehicle trajectory optimization along signalized arterial: A decentralized approach under mixed traffic environment

Qinzheng Wang^a, Yaobang Gong^a, Xianfeng Yang^{b,*}

^a Department of Civil & Environmental Engineering, University of Utah, 110 Central Campus Drive, Salt Lake City, UT 84112, United States

^b Department of Civil & Environmental Engineering, University of Maryland, College Park, 1173 Glenn Martin Hall, College Park, MD 20742, United States

ARTICLE INFO

Keywords:

Signalized arterial
connected automated vehicles
Trajectory optimization
Decentralized control

ABSTRACT

Trajectory optimization, as a key connected automated vehicles (CAVs) operation task, has the potential to mitigate traffic congestion, lower energy consumption, and increase the efficiency of traffic operation. This study proposes a decentralized approach to optimization CAV trajectories in both longitudinal and lateral dimensions along a signalized arterial under the mixed traffic environment, where human vehicles (HVs) and CAVs co-exist. More specifically, a 2-stage model is developed to optimize CAV trajectories based on traffic signal plans of downstream intersections and trajectory information of surrounding vehicles. The stage-1 is formulated to provide a rough estimate of the minimal travel time required for a single CAV traveling along this arterial with minimum stops. The stage-2 model is then designed to optimize the longitudinal and lateral behavior of CAVs with the objective of minimizing delay and lane-changing costs. This model is solved by a dynamic programming algorithm to satisfy the real-time optimization needs. A rolling horizon approach is adapted to dynamically implement the proposed model in light of changing traffic conditions. Numerical experiments have been conducted on a real-world arterial to evaluate the model performances. By comparing the optimized trajectories to the no optimization benchmark, the proposed model can reduce average stop delays of CAVs. Moreover, it can also reduce the stop delays of HVs and mixed traffic.

1. Introduction

Traffic conflict points (e.g., intersections, freeway merges, etc.) frequently cause vehicles to make numerous stop-and-go maneuvers (Li et al., 2010; Wang et al., 2021). Stop-and-go traffic results in a number of negative impacts, including increased traffic delay, excessive energy consumption and emissions, and boosted safety concerns (Li et al., 2019). Several solutions, including traffic signal control, ramp metering, work-zone management, etc., have been proposed to schedule the right of way of conflicting vehicles to mitigate such negative impacts. However, the effectiveness of those control strategies is limited because they can only guide or adjust the behavior of human-drivers rather than controlling vehicle movements directly. Fortunately, recent advances in connected automated vehicles (CAVs) technologies render it possible to implement vehicle movement/trajectory control directly. CAV is a

* Corresponding author.

E-mail addresses: qinzheng.wang@utah.edu (Q. Wang), yaobang.gong@utah.edu (Y. Gong), xyang@umd.edu (X. Yang).

combination of connected vehicle (CV) and automated vehicle (AV). Using CV technology, real-time information can be transmitted through both vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) channels. AV technology is capable of making precise vehicle level controls. As a result, the combination of them provides technical support for implementing information-based vehicle trajectory control.

In the literature, CAV trajectory optimization at intersections has received increasing attention and interest. [Feng et al. \(2018\)](#) applied optimal control theory to regulate the trajectory of platoon leading vehicles with the objective of minimizing fuel consumption and emission, while the trajectories of the following vehicles are captured by a car-following model. Leveraging the same method, [Yu et al. \(2018\)](#) designed vehicle trajectories based on optimized vehicle arrival times. [Zhou et al. \(2017\)](#) proposed a parsimonious shooting heuristic algorithm for designing vehicle trajectories for a stream of vehicles considering several boundary conditions. In a later study on the basis of the same algorithm, [Ma et al. \(2017\)](#) developed a holistic optimization model to determine vehicle trajectories with the optimal performance in terms of mobility, environment, and safety. To summarize, these studies were performed in a fully CAV environment. Moreover, the design of vehicle trajectory in those studies signal timing information. Some studies, on the other hand, do not require the use of traffic signals to design CAV trajectories. By assuming a fully CAV environment, those studies developed the concept of “signal-free”. Among those studies, one direction is based on some reservation scheme. When vehicles approach the intersection, they transmit information to the central controller to request reservations of space and time slots. Requests may be accepted or rejected based on a variety of rule-based policies, such as the “first-come, first-serve” (FCFS) strategy ([Dresner and Stone, 2008](#); [Au and Stone, 2010](#); [Li et al., 2013](#); [Zhang et al., 2016](#)), planning-based strategy ([Zhang et al., 2015](#)), or actuation-based strategy ([Carlino et al., 2013](#)). Another direction is based on the optimization models. In this category, researchers mainly developed models to optimize vehicle arrival times with the goal of minimizing delay ([Zohdy and Rakha, 2016](#); [Li et al., 2019](#)), travel time ([Fayazi and Vahidi, 2018](#); [Mirheli et al., 2019](#)), safety risk ([Lee and Park, 2012](#)), and energy consumption ([Zhang et al., 2016](#); [Malikopoulos et al., 2018](#); [Xu et al., 2018](#)). In summary, although existing studies can optimize CAV trajectories and enable them to travel across the intersection without stop, most models are based on a fully CAV environment. However, it is expected that the market penetration rate of CAVs will remain low in the near future due to technological and economical challenges ([Volpe National Transportation Systems Center, 2008](#)).

More recently, numerous studies have been conducted to optimize CAV trajectories at intersections under the mixed traffic environment. Such studies require taking into account the human vehicles (HVs). Accordingly, the majority of research began by predicting HV behaviors and then optimized CAV trajectories based on the prediction. [Yang et al. \(2016a, 2016b\)](#), firstly estimated the arrival sequence and trajectories of HVs using kinematic wave theory and Newell’s car following model. They proposed a bi-level model to optimize the CAV trajectories. The upper-level model is leveraged to optimize the vehicle departure sequence and then the lower-level model is developed to optimize the CAV trajectories according to the determined departure sequence. [Zhao et al. \(2018\)](#) applied an optimal velocity model to predict the HV behaviors. They assumed the preceding vehicle of each CAV travels at a constant speed. Therefore, the time for the CAV to arrive at the intersection during green time can be estimated. Then, they developed a model predictive control (MPC) method to enable a platoon of vehicles to pass the intersection on the green phase. [Pournmehrab et al. \(2019\)](#) predicted HV trajectories using the Gipps car-following model and then proposed a framework to adjust CAV trajectories to minimize total travel delay. [Yao and Li \(2020\)](#) also applied the Gipps car-following model to predict HV trajectories. Then, they proposed a decentralized control model to optimize CAV trajectories on a single-lane road to minimize travel time, fuel consumption, and safety risks. [Guo et al. \(2019\)](#) incorporated dynamic programming and shooting heuristic to propose an efficient DP-SH algorithm to optimize CAV trajectories. In their study, vehicle detectors are assumed to be installed upstream of the intersection at the beginning of the trajectory control section to obtain the HVs entry boundary information. Based on this, they proposed HVs shooting heuristic algorithm to predict their trajectories. [Jiang et al. \(2017\)](#) developed an eco-driving system to optimize CAV trajectories with the objective to improve fuel efficiency. The future HV trajectories are predicted by using the Intelligent Driver Model based on the collected current state of HVs, signal timing, and trajectory information of the preceding vehicle. The aforementioned studies have demonstrated that trajectory optimization strategies can improve the performance of CAV in terms of traffic delay, fuel consumption, and safety. However, they involve two main limitations: (a) those studies are only designed for isolated intersections; (b) those studies assume there is only one lane at intersections, or they only consider longitudinal optimization of CAV trajectories without considering lane-changing behavior, which is inappropriate in the real world. Until now, few studies have been conducted to optimize CAV trajectories considering lane-changing behavior. [Ma et al. \(2021\)](#) developed a bi-level optimization model to optimize CAV trajectories in both the longitudinal and lateral dimensions based on the signal timing and the predicted trajectories of surrounding vehicles. In this model, the upper level is to optimize lateral lane-changing strategies and the lower level is used to optimize longitudinal acceleration profiles. While this study considered the lateral behavior, it is still designed for the scenario with isolated intersections.

To the best of our knowledge, there is only a limited number of studies on CAV trajectory optimization along an arterial with multiple adjacent intersections. [He et al. \(2015\)](#) proposed a multi-stage optimal control model to optimize vehicle speed trajectory on signalized arterials considering both signal timing and queue impacts. [Huang and Peng \(2017\)](#) also developed a strategy to optimize vehicle speed trajectory to minimize fuel consumption and travel time considering the traffic signal information. However, these two studies were only applied to one individual vehicle. [Zhao et al. \(2018\)](#) investigated the coordination of a number of CAVs travelling through a corridor. They derived a closed-form analytical solution considering interior boundary conditions. This strategy can provide optimal trajectory for the entire route of the vehicle. [Wang et al. \(2019\)](#) proposed a cluster-wise cooperative eco-approach and departure applications for CAVs traveling along signalized arterials. This application consists of different stages, initial vehicle clustering, intra-cluster sequence optimization, cluster formation control, and cooperative eco-approach and departure. By incorporating those stages, energy consumptions and pollutant emissions of CAVs can be reduced. [Du et al. \(2018\)](#) proposed a hierarchical distributed coordinated strategy for CAVs to travel through multiple unsignalized intersections. This hierarchical structure includes three layers.

First, the road desired average velocity considering both upstream and downstream traffic is evaluated. Second, the reference velocity is assigned to each vehicle. Finally, fast model predictive control is applied for each vehicle to track their reference velocity in a computationally efficient manner. However, those studies are conducted based on the assumption that the market penetration rate is 100 %. [Wan et al \(2016\)](#) conducted a study on optimal speed advisory for connected traveling along an arterial. They formulated the speed advisory system as an optimal control problem. Then they achieved the general structure of fuel optimal solution analytically. They leveraged several microsimulation case studies to demonstrate that vehicles equipped with a speed advisory system can decrease fuel consumption significantly and the conventional vehicles can also have better energy efficiency. [Yu et al \(2019\)](#) proposed a mixed-integer linear programming model to cooperatively optimize CAV trajectories along an arterial. In this study, they considered not only the longitudinal optimization but also the lateral optimization. However, they assumed a 100 % market penetration rate of CAVs. Besides, although they designed the concept for CAV trajectory optimization along an arterial, the model implementation is still at the intersection level.

To summarize, notwithstanding the abundant studies on the optimization of CAV trajectories, it is noted that most of them are designed for isolated intersections and there are several limitations: (i) the CAV market penetration rate of many studies is assumed to be 100 %; and (ii) most models only consider the longitudinal behaviors without involving lateral behaviors. Also, despite a few studies have been conducted to optimize CAV trajectories along an arterial, some of them focused on the design of trajectories for only one individual vehicle instead of studying the overall traffic and a 100 % CAV environment is often required. To fill those research gaps, this paper takes a further step to optimize CAV trajectories along an arterial under a mixed traffic environment. A 2-stage optimization model is proposed to cooperatively optimize both longitudinal and lateral trajectories in a decentralized way based on the signal timing and the surrounding vehicle information. The stage-1 model is constructed to roughly estimate the minimal travel time required for a single CAV traveling along this arterial with minimum number of stops caused by red signal phase. Then, the stage-2 model is formulated to optimize CAV trajectories by minimizing the stop delay and numbers of lane-changing maneuvers. A dynamic programming (DP) algorithm is applied to solve this model and a rolling horizon method is designed to apply this algorithm considering the time-varying traffic condition.

The remainder of this paper is organized as follows. [Section 2](#) presents the general problem nature. [Section 3](#) builds the 2-stage model to optimize CAV trajectories along an arterial and the implementation procedure of the proposed model. [Section 4](#) conducts the numerical study. Finally, conclusions and recommendations for future study direction are summarized in section 5.

2. Problem statement

[Fig. 1](#) illustrates the CAV trajectory optimization problem along an arterial with several signalized intersections. Nodes in this figure represent intersections (i.e., the red nodes) and origins/destinations of vehicles entering/exiting this arterial (i.e., the blue nodes). The edge between two adjacent nodes is the road that vehicles travel on. By connecting a sequence of roads, we can obtain the paths that vehicles travel along this arterial. The orange dash arrow is a travel path example. Indeed, each path along this arterial can be divided into two distinct road types: links and connectors. The link is the road between the origin/destination and the intersection or between two intersections. The connector is the road that runs through the intersection and connects two continuous links.

To better understand the layout of the arterial and illustrate the subsequent problem, we take one intersection in [Fig. 1](#) as an example and depict it from a microscopic perspective. We assume that the travel path spans through this intersection, as illustrated in [Fig. 2](#). In this study, CAVs and HVs co-exist and travel along this arterial. As shown in [Fig. 2](#), there is a no-lane-changing zone near the intersection, which is a common practice in the real road network. If vehicles are required to make lane-changings, they must finish the maneuvers prior to entering this zone. In this study, we assume CAVs can collect real-time information about their surrounding HVs, including location, speed, acceleration, and lane choice, etc., through the onboard sensors. Additionally, CAVs can share the data with each other and collect the signal timing information. Then, using the real-time vehicle information and signal timing plan collected, CAV trajectories along this arterial can be controlled to achieve certain objectives.

Since then, numerous studies have been conducted to optimize CAV trajectories in a centralized mode ([Ma et al., 2017; Zhou et al., 2017; Wei et al., 2017; Wang et al., 2018](#)). While centralized control can result in optimal system performance, the computational efficiency is low and the costs of the coordination of the central controller are high. Compared with the centralized control, numerous studies have proved that a decentralized control is more appropriate for CAVs to achieve real-time automation ([HomChaudhuri et al., 2016; Yang et al., 2016a, 2016b; Malikopoulos et al., 2018; Mahbub et al., 2019; Mirheli et al., 2019; Yao and Li, 2020](#)). Therefore, this

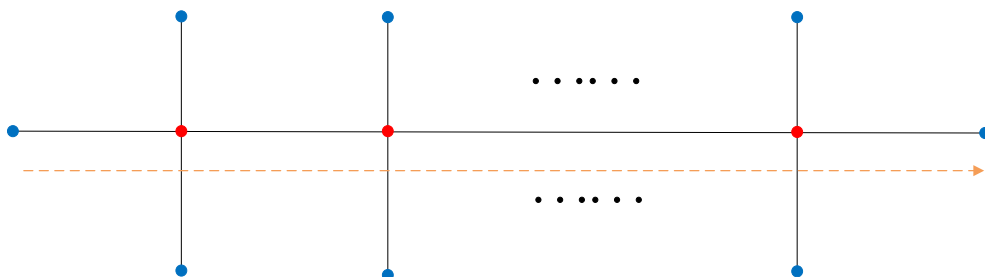


Fig. 1. A simple arterial with several signalized intersections.

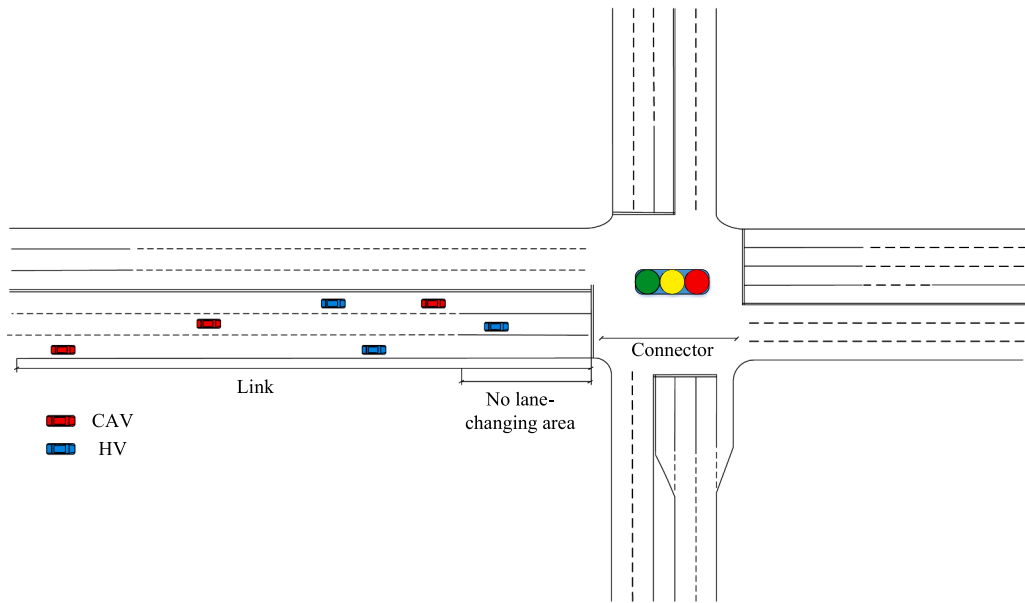


Fig. 2. An example intersection of CAV trajectories optimization.

study leverages the decentralized mode to optimization CAV trajectories. In other words, each CAV can be regarded as an intelligent device and optimized by itself. CAV trajectories are optimized one by one based on their location distribution along the arterial in this study. More specifically, the closer the link is from the entrance to the arterial, the later the CAV on it is optimized. Moreover, on each link, the optimization sequence of CAV trajectories is based on the distance to the stop bar, the closer the CAV is to the stop bar, the

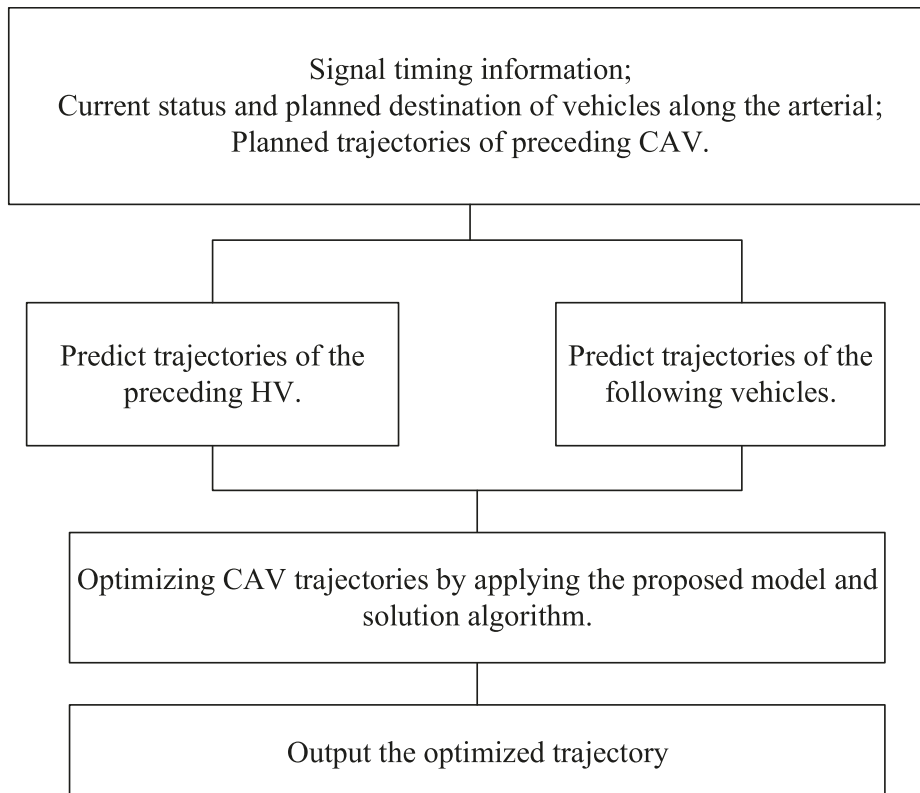


Fig. 3. The overall framework of CAV trajectories optimization.

earlier it will be optimized. The detailed optimization strategy is summarized as shown in Fig. 3.

For a CAV indexed by i , its surrounding vehicles can be classified into two categories: preceding vehicles Λ_i^P and the following vehicles Λ_i^F . The elements in these two categories satisfy $x_{i,j}(k) > x_{i',j}(k), i' \in \Lambda_i^P$ and $x_{i',j}(k) < x_{i,j}(k), i' \in \Lambda_i^F$, where $x_{i,j}(k)$ is the location of vehicle i on link j at time step k . The preceding vehicles include the preceding CAVs $\Lambda_i^{P,C}$ and preceding HVs $\Lambda_i^{P,H}$ (i.e., $\Lambda_i^P = \Lambda_i^{P,C} \cup \Lambda_i^{P,H}$). When optimizing the trajectory of CAV i , the future trajectories of its preceding CAVs are already planned and shared with it due to the optimization sequence as stated above. In this study, we applied a car-following model and a lane-changing model to predict the future trajectories of its preceding HVs. Moreover, the future trajectories of its following vehicles are predicted using the same car-following model and lane-changing model. The predicted future trajectories are shared with CAV i and then CAV i can dynamically optimize its trajectory in real-time. Notably, the planned trajectory of CAV i doesn't affect the operation of its preceding

Table 1
Summary of Key Notations.

General notations	
i	Vehicle index
j	Link index
z	Speed collection interval
Λ	Set of vehicles along the arterial
Λ_i^P	Set of preceding vehicles of CAV i . It includes the preceding CAVs ($\Lambda_i^{P,C}$) and preceding HVs ($\Lambda_i^{P,H}$) (i.e., $\Lambda_i^P = \Lambda_i^{P,C} \cup \Lambda_i^{P,H}$).
Λ_i^F	Set of following vehicles of CAV i
Λ^C	Set of CAVs
C	Cycle length
G	Green time
N	Number of vehicles detected by the detector during each time interval
p^i	Path of CAV i
M	A sufficiently large number
m	Lane number
M_j	Set of lanes on link or connector j
J^L	Set of links
J^C	Set of connectors
J	Set of links and connectors, where $J = J^L \cup J^C$
L_j	Length of link or connector j
Parameters	
Δt	Length of each time step
K^i	Trajectory planning horizon of CAV i
x_{safe}	Safe driving distance between two adjacent vehicles on the same lane
L_{NC}	Length of the area that vehicle cannot change lanes
t_{safe}	Safe time interval between two consecutive lane changings
τ	Reaction time
v_{thre}	Threshold of speed difference between two consecutive time steps
v_{min}	Minimum vehicle travelling speed
k_{lc}	Lane changing time step
v_{max}	Maximum vehicle travelling speed
a_{min}	Minimum deceleration
a_{max}	Maximum acceleration
Variables	
$t_{i,p}^0$	Travel time of vehicle i traveling along path p without or with minimum stops
$v_{i,j}$	Constant travel speed of CAV i on edge j
$t_{i,j}$	Travel time of vehicle i on link or connector j
$t_{i,j}^+$	Time that CAV i will arrive at the stop bar of link j
$t_{i,j}^-$	Time that CAV i starts to enter link j
$\bar{v}_j(z)$	Average speed of vehicles on link j during the z th time interval
$v_i(z)$	Detected travel speed of vehicle i during time interval z
$t_{i,p'}$	Travel time that CAV i traveling along path p'
$x_{i,j}(k)$	Location of vehicle i on link j at time step k . It represents the distance to the start of the link.
$X_{i,j}(k)$	Location relative to the entering point of this arterial
$x_{i,l}(k)$	Location of the following vehicle of vehicle i on the lane to which vehicle i will change
$x_{i,l'}(k)$	Location of the preceding vehicle of vehicle i on the lane to which vehicle i will change
$v_{i,j}(k)$	Speed of vehicle i on link j at time step k
$a_{i,l}(k)$	Acceleration/deceleration of vehicle i on link j at time step k
$\delta_{i,j}(k)$	Binary variable. If vehicle i changes lane on link j at time step k , $\delta_{i,j}(k) = 1$; $\delta_{i,j}(k) = 0$, otherwise
$\varepsilon(k)$	Binary variable. If CAV is still on the arterial at time step k , $\varepsilon(k) = 1$; $\varepsilon(k) = 0$, otherwise
$\beta_{i,j}(k)$	Binary variable. If vehicle i is on link or connector j , $\beta_{i,j}(k) = 1$; $\beta_{i,j}(k) = 0$, otherwise
$\delta_{i,m,j}(k)$	Binary variable. If vehicle i is on lane m of link or connector j at time step k , $\delta_{i,m,j}(k) = 1$; $\delta_{i,m,j}(k) = 0$, otherwise
$q_{i,i'}(k)$	Binary variable. If vehicle i is in front of vehicle i' , $q_{i,i'}(k) = 1$, $q_{i,i'}(k) = 0$; otherwise
$\varphi_{i,j}$	Binary variable. If vehicle have passed link j , $\varphi_{i,j} = 1$; otherwise, $\varphi_{i,j} = 0$.
σ_i	Binary variable. If vehicle i is the first vehicle on the lane, $\sigma_i = 1$; otherwise, $\sigma_i = 0$

vehicles but would affect the driving behaviors of its following vehicles.

3. Methodology

This section introduces the 2-stage model to optimize CAV trajectories under a series of conditions. The longitudinal and lateral behaviors are considered and then the longitudinal location and lane-changing behavior are optimized for each CAV. For the convenience of discussion, key notations of the proposed model are summarized in Table 1.

3.1. Optimization model

3.1.1. Stage-1 model

In the literature, most studies optimized CAV trajectories with the objective of minimizing the total travel time. While this may be an advantageous strategy for vehicles to travel across an isolated intersection, it may exert negative impacts on the driving experience when traveling along an arterial. As shown in Fig. 4, the orange line is the vehicle trajectory traveling along this arterial with minimal travel time. It can be observed that this vehicle needs to stop at each intersection according to this designed trajectory. In contrast, if the trajectory is designed as the blue line shown in Fig. 4, although the minimum travel time is not achieved, the vehicle could travel along the arterial without the interruption of the red signals. This is the primary goal of several arterial management strategies, such as the traffic signal progression. Therefore, the primary objective of this study is to optimize CAV trajectories and minimize the number of stops caused by red signal phases.

To such a need, the proposed model will optimize the trajectory of each CAV at each time step, considering the entire period when it is on the studied arterial segment. However, it can be expected that such an optimization will result in a huge computation burden. Moreover, due to the time-varying traffic conditions, it is challenging to enable each CAV to travel along the arterial without stops at each time step. To tackle those issues, this study develops a 2-stage framework, where the stage-1 model is to roughly estimate the minimal time that a vehicle may take to pass the arterial segment when its number of stops is minimized. Then, the stage-2 model is to optimize CAV trajectories using a rolling horizon scheme that takes time-varying conditions into account. The stage-1 model is constructed on the assumption that CAVs do not consider driving impacts of other vehicles and can maintain a constant travel speed on each link. Then the stage-1 model is formulated in Eqs. (1) – (7).

$$\min(\omega_1 t_{i,p^i}^0 + \sum_{l \in p^i} \omega_2 (v_{i,j} - \bar{v}_j(z))) \quad (1)$$

$$t_{i,p^i}^0 = \sum_{j \in p^i} t_{i,j}, i \in \Lambda^C, j \in p^i \quad (2)$$

$$t_{i,j} = \frac{L_j}{v_{i,j}}, i \in \Lambda^C, j \in p^i \quad (3)$$

$$\bar{v}_j(z) = \frac{1}{N} \sum_{i=1}^N v_i(z), i \in \Lambda, j \in p^i \quad (4)$$

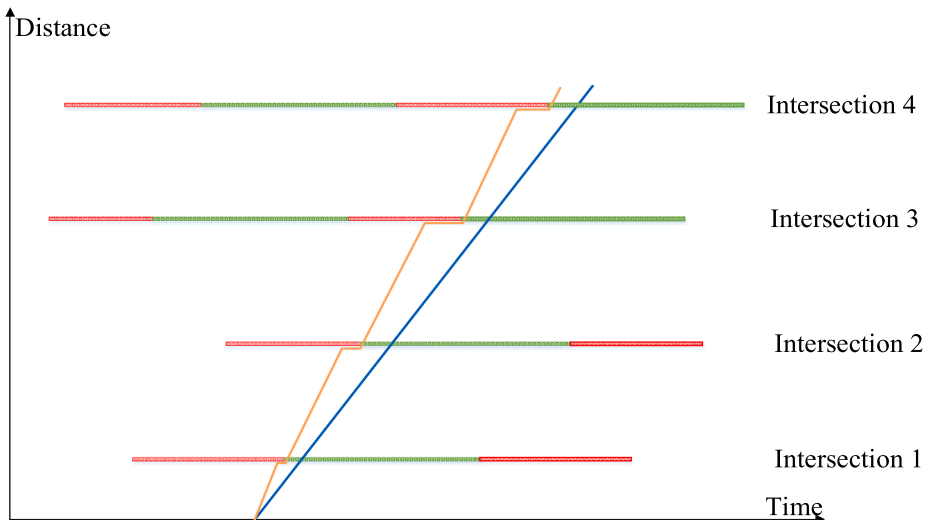


Fig. 4. An illustration of a vehicle traveling along an arterial.

$$t_{ij}^+ = t_{ij}^- + t_{ij}, i \in \Lambda^C, j \in p^i \quad (5)$$

$$G(t_{ij}^+) = \begin{cases} t_{ij}^+ & \text{if } \text{mod}(t_{ij}^+, C) \in [0, G] \\ \lceil t_{ij}^+ / C \rceil * C, & \text{otherwise} \end{cases} \quad (6)$$

$$v_{\min} \leq v_{ij} \leq v_{\max} \quad (7)$$

Eq. (1) is the objective function of minimizing the travel time of CAVs along the arterial and speed oscillation amplitude, where ω_1 and ω_2 are weighting parameters ($\omega_1 \gg \omega_2$ to differentiate the importance of the objectives). t_{i,p^i}^0 is the travel time of vehicle i , along path p^i , when its minimal number of stops is achieved. It can be determined by summing up the travel time on each link and connector along the path, as shown in Eq. (2). In Eq. (3), t_{ij} is the travel time of vehicle i on link j , where its value is estimated when the CAV arrives at the link, v_{ij} is the constant travel speed of vehicle i on link j , and Λ^C is the set of CAVs. The travel time on the connector is not consider due to the short travel distance. Eq. (4) aims to calculate $\bar{v}_j(z)$, which is defined as the average speed of vehicles on link j during the z th time interval. In this study, we assume detectors are installed in the middle of each link to collect the speed of each vehicle. Herein, $v_i(z)$ is the collected speed by the detector during the z th time interval and N denotes the number of vehicles detected. Eq. (5) is to estimate the time that CAV i will arrive at the stop bar of link j , represented by t_{ij}^+ , where t_{ij}^- is the time that CAV i starts to enter link j . Eq. (6) is used to estimate the optimal vehicle travel time along the link that can ensure the passing during green signal phase, where C denotes the cycle time and G is the green time. Eq. (7) is the speed constraint. Notably, when no feasible solution could be found, the proposed model will select the default speed (e.g., the speed limit) directly to calculate the required link travel time at this stage.

3.1.2. Stage-2 model

The stage-2 model is constructed to optimize the longitudinal and lateral driving behavior based on the solution from the stage-1. More specifically, this study considers the optimal vehicle travel time along the link as the optimization target for allowing vehicles to pass the intersection during green signal phases. Then, the objective of the stage-2 model is to minimize the difference between the ideal and actual link travel times, and lane-changing numbers, as shown in Eq. (8).

$$\min(\omega_3(t_{i,p^i} - t_{i,p^i}^0) + \omega_4 \sum_{j \in p^i} \sum_{k \in K^i} \vartheta_{ij}(k)) \quad (8)$$

where t_{i,p^i} is the actual travel time that CAV i traveling along path p^i . Notably, the ideal travel time, t_{i,p^i}^0 , is obtained from stage-1 model which assumes a free-flow traffic condition. Hence, the difference ($t_{i,p^i} - t_{i,p^i}^0$) could be viewed as a travel delay indicator. The secondary objective function term is to minimize the number of lane-changing maneuvers. This is to improve the smoothness of the lateral trajectory. Here, $\vartheta_{ij}(k)$ is an auxiliary binary variable to indicate if vehicle i changes lane on link j at time step k . If vehicle i changes lane on link j at time step k , $\vartheta_{ij}(k) = 1$; $\vartheta_{ij}(k) = 0$, otherwise. ω_3 and ω_4 are weighting parameters and $\omega_3 \gg \omega_4$ to differentiate the importance of the objectives.

Note that the first objective function term makes this model difficult to solve. Therefore, we discretize the period and then it can be reformulated as:

$$t_{i,p^i} = \sum_{k=0}^{K^i} \varepsilon(k) * \Delta t, i \in \Lambda^C, k \in K^i \quad (9)$$

where, $\varepsilon(k)$ is an auxiliary binary variable to indicate whether CAV i is still on the arterial at time step k . If yes, $\varepsilon(k) = 1$; otherwise, $\varepsilon(k) = 0$. K^i is the trajectory planning horizon of CAV i . Other constraints are described in the following part.

Longitudinal vehicle dynamics.

For safety concerns, vehicles are not allowed to move backward on links and connectors along the arterial:

$$x_{ij}(k+1) \leq x_{ij}(k), i \in \Lambda, j \in p^i, k \in K^i \quad (10)$$

where $x_{ij}(k)$ is the location of vehicle i on link or connector j at time step k . Eq. (10) is used to ensure the vehicle to be closer to its destination when traveling along the arterial and to avoid unregular driving behaviors that might cause collisions.

Vehicles are supposed to be on the link or connector of this arterial until they reach their destinations. This can be ensured by Eq. (11):

$$M * (\beta_{ij}(k) - 1) \leq x_{ij}(k) \leq L_j * \beta_{ij}(k), i \in \Lambda, j \in p^i, k \in K^i \quad (11)$$

where, $\beta_{ij}(k)$ is an auxiliary binary variable. If vehicle i is on link or connector j , $\beta_{ij}(k) = 1$; $\beta_{ij}(k) = 0$, otherwise.

Vehicles can only occupy one lane at each time step during the trajectory planning horizon:

$$\sum_{m \in M^i} \delta_{i,m,j}(k) = 1, i \in \Lambda, j \in p^i, k \in K^i \quad (12)$$

where, $\delta_{i,m,j}(k)$ is an auxiliary binary variable. If vehicle i is on lane m of link or connector j at time step k , $\delta_{i,m,j}(k) = 1$; $\delta_{i,m,j}(k) = 0$,

otherwise.

To maintain the stability of the vehicle operation, the following constraint should be satisfied.

$$|v_{ij}(k+1) - v_{ij}(k)| \leq v_{thre} \quad (13)$$

where v_{thre} is the threshold of the speed difference between the two consecutive time steps.

Longitudinal safety.

When vehicles are on the same lane along an arterial, it should keep a safe distance with its preceding vehicle and its following vehicle. When vehicle i and vehicle i' are on the same link, Eq. (14) and Eq. (15) should be satisfied.

$$(3 - \delta_{i,mj}(k) - \delta_{i',mj}(k) - q_{i,i'}(k)) * M + X_{ij}(k - \frac{\tau}{\Delta t}) - X_{i',j}(k) \geq x_{safe}, i \in \Lambda, j \in p^i, k \in K^i \quad (14)$$

$$(2 - \delta_{i,mj}(k) - \delta_{i',mj}(k) - q_{i,i'}(k)) * M + X_{i',j}(k - \frac{\tau}{\Delta t}) - X_{ij}(k) \geq x_{safe}, i \in \Lambda, j \in p^i, k \in K^i \quad (15)$$

where $q_{i,i'}(k)$ is an auxiliary binary variable that defines the order between vehicle i and vehicle i' on the same lane. If vehicle i is in front of vehicle i' , $q_{i,i'}(k) = 1$, $q_{i,i'}(k) = 0$; otherwise. τ is the reaction time. $X_{ij}(k)$ is the location relative to the entering point of this arterial. As shown in Fig. 5, the location of vehicle i on link j at time step k is $x_{ij}(k)$ and its relative location should be $L_1 + L_2 + L_3 + L_4 + x_{ij}(k)$. Then, the relative location can be represented by Eq. (16).

$$X_{ij}(k) = \sum_{j=1}^n \varphi_{ij} * L_j + \sum_{j=1}^n \beta_{ij}(k) * x_{ij}(k), i \in \Lambda, j \in p^i, k \in K^i \quad (16)$$

where φ_{ij} is an auxiliary binary variable to describe if vehicle have passed link j . If yes, $\varphi_{ij} = 1$; otherwise, $\varphi_{ij} = 0$.

If vehicle i is on the link and vehicle i' is on the connector, as shown in Fig. 7, Eqs. (14)-(15) can still ensure the safety gap between the two vehicles.

Considering the impacts of red indication of traffic signals, Eq. (16) should be satisfied.

$$x_{ij}(k) \leq L_j + M(2 - r(k) - \sigma_i), i \in \Lambda, j \in p^i, k \in K^i \quad (17)$$

where L_j is the length of link j . $r(k)$ is an auxiliary binary variable to indicate the status of traffic signals. If the traffic signal indicates red at time step t , $r(k) = 1$; otherwise, $r(k) = 0$. σ_i is another auxiliary binary variable to determine the location of vehicle i . If vehicle i is the first vehicle on the lane, $\sigma_i = 1$; otherwise, $\sigma_i = 0$. By defining those variables, Eq. (17) can ensure vehicle i would travel through the intersection when the traffic signal is green and stop when the traffic signal is red.

Lateral operation.

In this paper, we assume that vehicles can finish lane-changing within one time step.

$$(\delta_{i,m',j}(k+1) - \delta_{i,m,j}(k)) * \theta_i(k) = 0, i \in \Lambda, j \in p^i, k \in K^i, m_j, m'_j \in M^j, m'_j \neq m_j$$

If vehicle i plans to change lanes at time step k , it can only change to its adjacent lane during this lane-changing maneuver for safety concern.

$$(\delta_{i,m',j}(k+1) - \delta_{i,m,j}(k)) * \theta_i(k) + |m_j - m'_j| = 1, i \in \Lambda, j \in p^i, k \in K^i, m, m' \in M^j, m'_j \neq m_j \quad (19)$$

where m_j and m'_j are lane number. In this paper, the lane number increases from the outermost lane to the innermost lane.

The lane-changing maneuver is forbidden for vehicle i if it stops.

$$-M(x_{ij}(k+1) - x_{ij}(k)) \leq \delta_{i,m,j}(k+1) - \delta_{i,m,j}(k) \leq M(x_{ij}(k+1) - x_{ij}(k)), i \in \Lambda, j \in p^i, k \in K^i, m \in M^j \quad (20)$$

Vehicles are not allowed to change lanes when they are close to the stop bar at each intersection along this arterial, which is a common practice in the real road network.

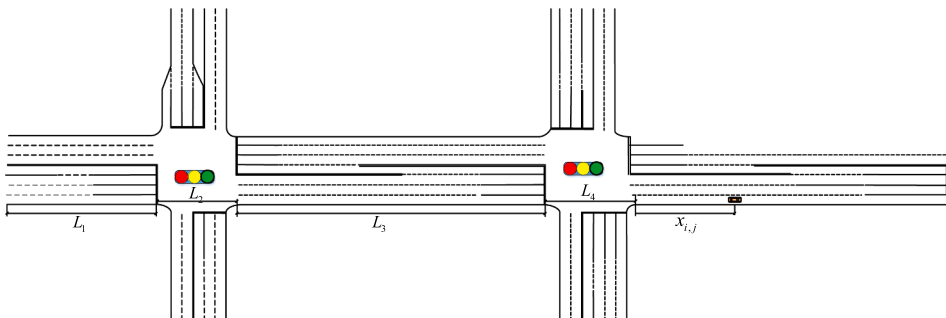


Fig. 5. Relative location of a vehicle.

$$L_{NC} - x_{ij}(k) \leq M^*(1 - |\delta_{i,m,j}(k+1) - \delta_{i,m,j}(k)|), i \in \Lambda, j \in J^L, k \in K^i, m \in M^i \quad (21)$$

where L_{NC} is the length of the region that vehicles cannot change lanes.

In this paper, vehicles are also not allowed to change lanes on connectors for safety concern:

$$(\delta_{i,m,j}(k+1) - \delta_{i,m,j}(k)) = 0, i \in \Lambda, j \in J^C, k \in K^i, m \in M^i \quad (22)$$

Lateral safety.

For safety concerns, if a vehicle plans to change lanes, the space in the target lane for lane-changing should be sufficiently large to avoid collisions:

$$(1 - \vartheta_i(k))^*M + x_{ip,l}(k) - x_{il}(k) \geq x_{safe}, i \in \Lambda, j \in p^i, k \in K^i, m \in M^i \quad (23)$$

$$(1 - \vartheta_i(k))^*M + x_{il}(k) - x_{ip,l}(k) \geq x_{safe}, i \in \Lambda, j \in p^i, k \in K^i, m \in M^i \quad (24)$$

where, $x_{ip,l}(k)$ is the location of the preceding vehicle of CAV i on the target lane if at time step k CAV i changes lanes; $x_{il}(k)$ is the location of the following vehicle of CAV i on the target lane if at time step k CAV i changes lanes; and x_{safe} is the safe space for lane-changing, which includes the distance between this vehicle and the preceding vehicle and following vehicle on the adjacent lanes.

When a vehicle finishes changing lane, it should keep a safe distance with its preceding vehicle and following vehicle:

$$x_{il}(k + k_{lc}) \geq x_{ip,l}(k) + v_{ip,l}(k)^*k_{lc} + \frac{1}{2}a_{ip,l}(k)^*k_{lc}^2 + M(\vartheta_i(k) - 1), i, i_p, i_f \in \Lambda, j \in J, k \in K^i \quad (25)$$

$$x_{ip,l}(k + k_{lc}) \leq x_{il}(k) + v_{il}(k)^*k_{lc} + \frac{1}{2}a_{il}(k)^*k_{lc}^2 + M(\vartheta_i(k) - 1), i, i_p, i_f \in \Lambda, j \in J, k \in K^i \quad (26)$$

The time interval between the consecutive lane-changing maneuvers should be constrained to avoid a high frequency of such behaviors:

$$M^*(2 - \vartheta(k_1) - \vartheta(k_2)) + (k_1 - k_2)^*\Delta t \geq t_{safe}, k_1, k_2 \in K^i \quad (27)$$

where t_{safe} is the minimum time between two consecutive lane-changing maneuvers.

Longitudinal vehicle kinematics.

In this paper, we apply the second-order vehicle kinematics model to describe the longitudinal movement dynamics of vehicles, as shown below:

$$v_{ij}(k+1) = v_{ij}(k) + a_{ij}(k)^*\Delta t, k \in K^i \quad (28)$$

$$x_{ij}(k+1) = x_{ij}(k) + \frac{1}{2}a_{ij}(k)^*(\Delta t)^2, k \in K^i \quad (29)$$

$$0 \leq v_{ij}(k) \leq v_{max} \quad (30)$$

$$a_{min} \leq a_{ij}(k) \leq a_{max} \quad (31)$$

3.2. Solution algorithm

As aforementioned, the optimization of CAV trajectories should include two procedures. First, future trajectories of other vehicles should be predicted. Second, the CAV trajectory is optimized based on the predicted trajectories. They are specified in the following part.

3.2.1. Vehicle trajectory prediction

To optimize the trajectory of a CAV i , trajectories of its adjacent vehicles need to be identified to determine the solution space. Therefore, what need to predict are trajectories of its preceding HVs and its all following vehicles (i.e. CAVs and HVs). The process of trajectory prediction is as follows:

Step 1: Obtain the current state (e.g., location, speed) of each vehicle at the current step k .

Step 2: Obtain the states of CAVs in Λ_i^P at the next step $k+1$ according to the optimized trajectories.

Step 3: Predict the longitudinal states of HV in Λ_i^P at time step $k+1$ one by one based on Wiedemann's car-following 74 model (Wiedemann, 1974). It divides the traffic state into four categories: free driving, closing in, following, and emergency state. For each state, it leverages different regimes to determine the future state of each vehicle. The lane-changing decision is based on Gipp's lane-changing model (Gipps, 1986).

Step 4: Predict the states of CAV i and vehicles in Λ_i^F . The prediction process is the same as that in step 3.

Step 5: Considering the model complexity and computational burden, we set the prediction length as T instead of the whole trajectory planning horizon. If $k^*\Delta t = T$, output the predicted trajectories. Otherwise, check if vehicle i still on the arterial at the time step $k+1$, then set $k = k+1$ and go back to step 2.

3.2.2. CAV trajectory optimization

CAV trajectories optimization is achieved by solving the proposed 2-stage model. In this paper, both stage-1 and stage-2 models are solved by applying dynamic programming (DP). For the stage-1 model, the travel speed without stops for each vehicle is roughly estimated when they arrive on each link for the first time. Based on the output, the stage-2 model is solved to obtain the control and lane-changing decisions. Due to the complexity of this model, we discretize the control variables (i.e., speed in the stage-1 model, and acceleration and deceleration rate in the stage-2) to make them solvable. The same method can be found in several existing studies (Wei et al., 2017; Wang et al., 2020).

The basic principle behind the DP algorithm is that a decision problem is broken into several manageable decision stages and the optimal performance is computed in a recursive manner. The recursion can be performed in a forward manner starting from the initial decision stage or in a backward manner from the final decision stage. In this paper, we adapt the forward manner. Based on this setting, the value function at any decision stage is an accumulated measure of the effectiveness of the current and all previous stages. In general, to specify a DP formulation, we must define several basic elements, including stage, control variable, state variable, performance measurement function, and value function.

In the stage-1, the recursion is based on using links for each path as stages. Starting with the initial link that CAVs on this arterial for the first time, DP treats each link of each path as a stage and optimizes within a control horizon to obtain the optimal plan. The index for stages at this level can be represented by n . Let x_n^U be the control variable denoting the travel speed for CAVs on stage n . The state variable is the set of available travel speeds for CAVs at stage n , denoted by s_n^U . We use $f(s_n^U, x_n^U)$ to denote the performance measurement cost given s_n^U and x_n^U , and use $v_n(s_n^U)$ to denote value function which is the cumulative value of prior performance cost. For the stage-2, the discretized time horizon is set as stages. Following the same way, DP regards each time step as a stage to achieve the optimal result starting from the initial time point. In this level, we use x_n^L to denote the control variable which is the combination of acceleration and lane-changing variable for CAVs at stage n , and s_n^L is the state variable denoting the combination of speed and locations of CAVs. $f(s_n^L, x_n^L)$ denotes the performance measurement cost given s_n^L and x_n^L , and $v_n(s_n^L)$ denotes value function. Based on those defined notations, the pseudo code for the stage-1 and stage-2 are shown below. For the stage-2, we consider a random planning horizon of H and step size ϵ , which reflects the generality of the algorithm.

DP algorithm for stage-1 model

```

Initialization:  $n = 1, s_0^U = 0, v_0(s_0) = 0$ 
for  $n = 0$  to  $N$ :
  for  $s_n^U$  in  $S_n^U // S_n^U$  is the value of state variable at stage  $n$ 
    while  $x_n^U$  in  $X_n^U(s_n^U) // X_n^U(s_n^U)$  is the set of control variables given state variable
      if  $g_{start} \leq t_{cur} + \frac{L_n}{x_n^U} \leq g_{end} //$  CAVs can travel within the green period
        calculate  $f(s_n^U, x_n^U)$ 
      Loop
         $v_n(s_n^U) = \min_{x_n^U} (f(s_n^U, x_n^U) + v_{n-1}(s_n^U))$ 
      record  $x_n^{*U}(s_n^U)$ 
    End
  For  $n = N$  to  $1$ :
    Trace back to find the optimal solution at each stage

```

DP algorithm for the stage-2 model.

Define time horizon as global variable

```

Initialization:  $n = 1, s_0^L = 0, v_0(s_0) = 0$ 
for  $n = 0$  to  $N$ :
  for  $s_n^L$  in  $S_n^L // S_n^L$  is the state of state variable at stage  $n$ 
    while  $x_n^L$  in  $X_n^L(s_n^L) // X_n^L(s_n^L)$  is the set of control variables given state variable
      if vehicle kinematics satisfies &
        if longitudinal safety satisfies and lateral safety satisfies:
          calculate  $f(s_n^L, x_n^L)$ 
        Loop
           $v_n(s_n^L) = \min_{x_n^L} (f(s_n^L, x_n^L) + v_{n-1}(s_n^L))$ 
        record  $x_n^{*L}(s_n^L)$ 
      if  $s_n^L$  doesn't satisfy longitudinal and lateral operation:
        continue
    End
  For  $n = N$  to  $1$ :
    Trace back to find the optimal solution at each stage

```

3.2.3. Rolling horizon scheme

Due to real-time varying traffic conditions, we apply a rolling horizon scheme to dynamically implement the trajectory optimization model. The basic logic of the rolling horizon scheme is to determine the optimal trajectory for a future time horizon at each time step considering the surrounding traffic environment, but the resulted optimization strategy is applied only over a much shorter time period. Such a scheme is adapted by CAV one by one according to their location distribution on this arterial. When the parameters such as planning time horizon are initialized, the trajectory optimization procedure for each CAV follows the algorithm depicted in [Section 3.2.1 and 3.2.2](#).

Based on the algorithm of vehicle trajectory prediction and dynamic programming, the process of CAV trajectories optimization can be summarized in [Fig. 6](#).

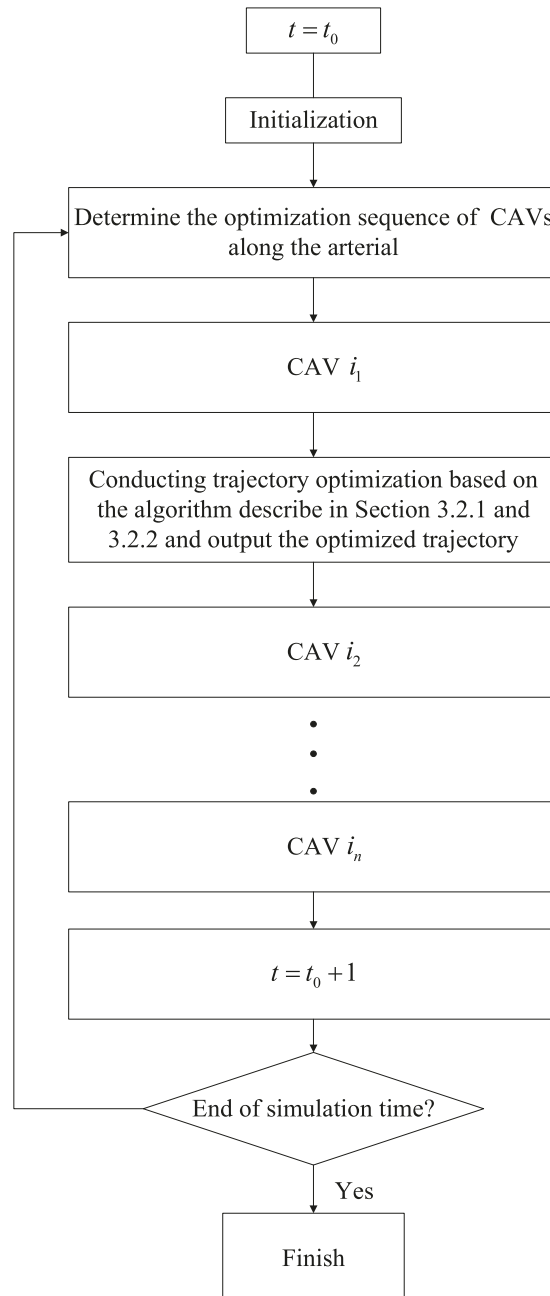


Fig. 6. Optimization framework of CAV trajectories.

4. Numerical examples

4.1. Experimental design

To evaluate the effectiveness of the proposed trajectory optimization model, we select a real-world network on Redwood Road in Salt Lake City, Utah for study. As shown in Fig. 7, this selected segment includes four intersections which are operated by the Utah Department of Transportation (UDOT). Considering the complexity of this problem, only through movements of one direction along this arterial are taken for the experiments.

To better illustrate the benefits of the proposed CAV trajectories planning strategy, both CAVs and HVs share the same parameters in driving behavior models. The maximum speed limit for CAVs is 60 km/h. The maximum acceleration rate for CAVs is 4 m/s^2 and the minimum acceleration rate for CAVs is -3 m/s^2 . The minimum time interval between two consecutive lane-changing behaviors of one vehicle is 5 s. The threshold of speed difference between two consecutive time steps is 10.8 m/s. The safe space for vehicles to conduct lane-changing is 6 m. The safe distance between two vehicles on the same lane is 6 m. The time step is 1 s. The planning horizon in the rolling horizon is 5 s.

To illustrate the effectiveness of the proposed CAV trajectories, we apply the scenario in which trajectories are not optimized as the benchmark for comparison. The simulation is conducted in VISSIM. Nine random seeds are used in the simulation and each simulation runs for 1800 s with a warm-up period of 300 s. Each seed is tested by four scenarios with 20 %, 25 %, 30 %, 35 %, and 100 % of CAV market penetration rates. Traffic demands are collected from Automated Traffic Signal Performance Measures (ATSPM) system which uses Wavetronix SmarterSensor Matrix detectors to collect and restore lane-by-lane turning counts. Raw data on August 2019 was extracted and peak period are selected for this study.

4.2. Result analysis

4.2.1. Benefits analysis for CAVs, HVs, and mixed traffic

In this section, experiments are conducted in mixed traffic with a 35 % market penetration rate to evaluate the proposed trajectory optimization strategy. Table 2 shows the average stop delays and average lane-changing numbers of CAVs, HVs, and mixed traffic.

As shown in Table 2, the proposed trajectory optimization strategy outperforms the benchmark in terms of stop delays for CAVs. This is because the proposed strategy could optimize CAV trajectories to make them travel along this arterial with fewer stops. It can be observed that the optimization strategy can also reduce the stop delays of HV and mixed traffic compared with the benchmark trajectories. Since some HVs follow the CAVs to travel along this arterial, their trajectories are similar to the optimized CAV trajectories, i. e., they can also travel through each intersection without stops. Then the stop delays of mixed traffic decrease due to the reduced stop delays of CAVs and HVs. Compared with the benchmark trajectories, the optimization of CAV trajectories can reduce the average stop delays of CAVs, HVs, and mixed traffic by 80.55 %, 24.12 %, and 43.49 %, respectively. We can observe that the average stop delays of CAVs decreased most. This is because the proposed trajectory optimization strategy is designed for CAVs and thus most CAVs can travel through each intersection without stops. Table 2 also demonstrates that the optimization of CAV trajectories produce a larger lane-changing numbers of CAVs compared with the benchmark. This is because the proposed strategy could enable CAVs to change lane to travel through the intersection during green time if there is a slow traffic on current lane. Besides, if there is a congestion traffic in front of CAVs, the proposed strategy could make CAVs change lane to avoid congestion as more as possible. Moreover, we can see that the average lane-changing numbers of HV increases compared with the benchmark. This is because the proposed strategy may enable CAVs in the upstream to slow down to across the intersection without stops. As a result, the following HV choose to change lanes to avoid collisions.

The above analysis can also be explained by visualizing CAV trajectories and HVs traveling along this arterial. Fig. 8 illustrates example CAV trajectories and HVs when the market penetration rate is 35 %. The CAV trajectories are plotted lane by lane. In each lane, there are two colors of lines. The trajectories of CAVs are marked in dark colors and the trajectories of HVs are marked in light colors. The dash line between different lanes indicates the lane changing maneuvers of CAVs. As we can see, most CAVs can travel along this arterial without stopping, and some HV following the CAVs also travel through some of those four intersections without stopping. To better illustrate the lane-changing maneuver of CAVs and HVs, we select part of Fig. 8 and amplify, as shown in Fig. 9 and

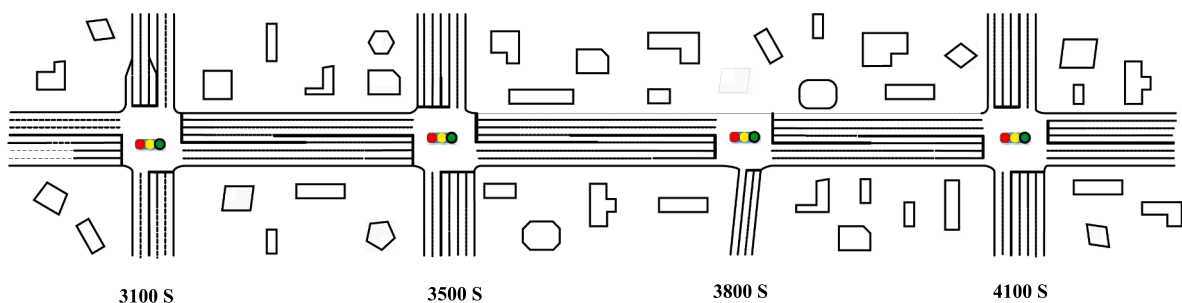


Fig. 7. The geometry layout of simulated arterial.

Table 2

Performance of the proposed trajectory optimization strategy.

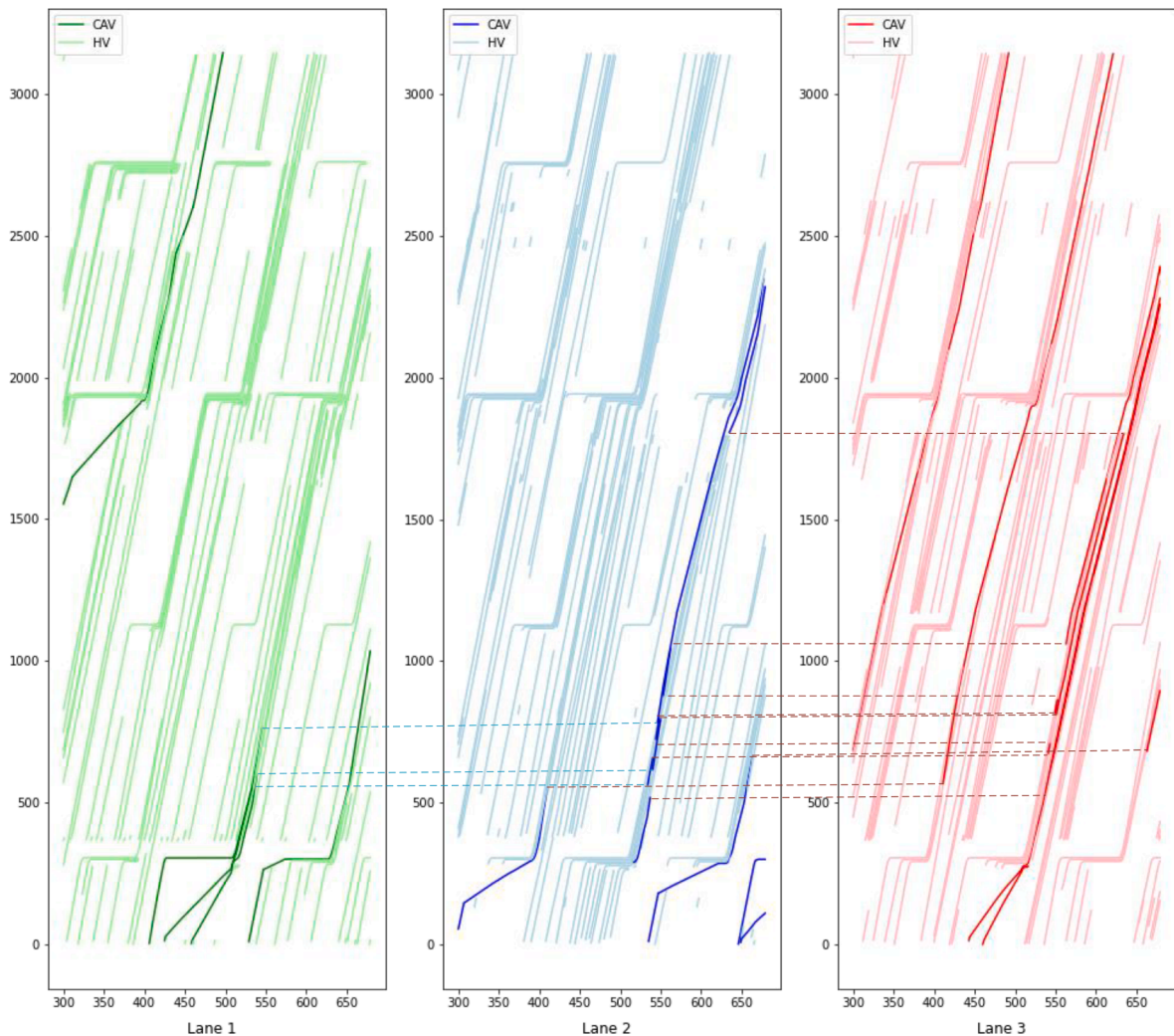
Vehicle type	Average stop delays (sec)		Average lane-changing numbers	
	Benchmark	Proposed model	Benchmark	Proposed model
CAV	60.47	11.71	2.896	2.673
HV	57.94	40.98	2.892	3.053
Mixed traffic	58.78	31.82	2.897	2.917

Fig. 10. As shown in Fig. 9, when there is enough space in the adjacent lane for the CAV to change lanes, the CAV can conduct a lane-changing maneuver according to the optimized trajectory. From Fig. 10, we can see that an HV on lane 3 was forced to change to lane 2 at around 600 s because of the lower speed of its preceding CAVs on lane 3.

4.2.2. Sensitivity analysis

To further validate the effectiveness of the proposed optimization strategy, we conduct the sensitivity analysis in terms of different market penetration rates. The proposed trajectory optimization strategy is tested in four scenarios with CAVs market penetration rates of 20 %, 25 %, 30 %, 35 %, and 100 %. The average stop delays and average lane-changing numbers under various market penetration rates are displayed in Table 3 and Table 4.

As shown in Table 3, the proposed trajectory optimization strategy outperforms the benchmark regarding average stop delays for CAVs, HVs, and mixed traffic under all scenarios with various market penetration rates. Moreover, with the increase of CAVs market penetration rate, the average stop delays decrease for CAVs, HVs, and mixed traffic. This is because a higher CAVs market penetration

**Fig. 8.** Spatial-temporal CAV trajectories and HVs in the mixed traffic.

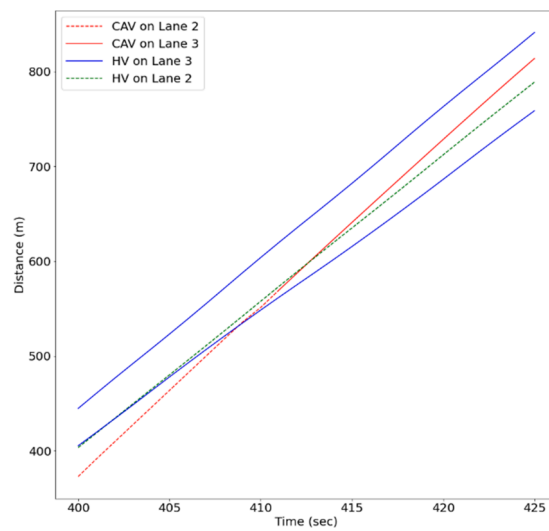


Fig. 9. Lane-changing of CAVs.

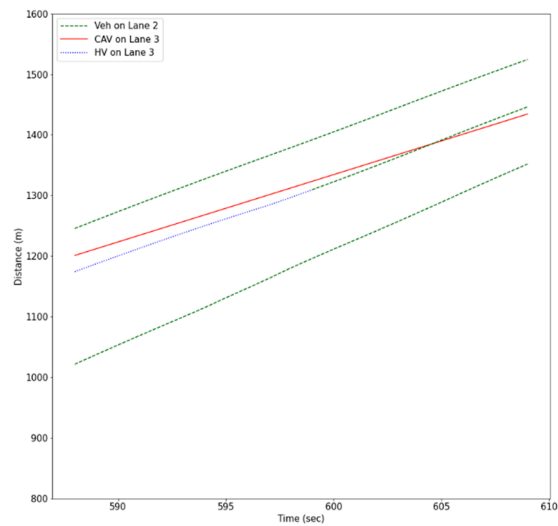


Fig. 10. Lane-changing of HVs.

Table 3

Average stop delays with various market penetration rate.

Market penetration rate	Strategies	Vehicle type		
		CAV	HV	Mixed traffic
20 %	Benchmark	61.89	56.93	57.84
	Proposed	16.44	42.43	38.01
25 %	Benchmark	63.89	56.12	57.92
	Proposed	13.86	41.77	35.49
30 %	Benchmark	62.45	56.13	58.06
	Proposed	12.61	41.46	33.47
35 %	Benchmark	60.47	57.95	58.78
	Proposed	11.71	40.98	31.82
100 %	Benchmark	61.18	/	61.18
	Proposed	9.07	/	9.07

rate means more CAVs traveling along the arterial, the trajectory optimization strategy can enable more CAVs travel along this arterial without stopping and more HVs following those CAV can also avoid stops. This indicates that trajectory optimization for CAVs has the potential to reduce the stop delays of HVs and mixed traffic when there are more CAVs in the mixed traffic. It can be observed from Table 4 that the proposed trajectory optimization strategy can lower the lane changing number of CAVs under all CAV market penetration rates compared with the benchmark. Moreover, trajectory optimization for CAVs could increase the lane-changing numbers of HVs under the market penetration rate of 20 %, 25 %, 30 %, and 35 %. This is also because the low speed of upstream CAVs with optimized trajectories forces their following HVs to change lanes.

We further conduct the testing under three traffic demand scenarios. Traffic data recorded by ATSPM are regarded as average demand. The cases of high demand and low demand are defined as being $\pm 20\%$ of average demand (Rafter et al., 2020), respectively. Those tests also reveal the performance sensitivity of the optimization strategy with different market penetration rates. The average stop delays under different penetration rates of various traffic demands are shown in Fig. 11.

As shown in Fig. 11, the average vehicle stops delays for CAVs, HVs, and mixed traffic rise with the increase of traffic demand. This is because higher traffic demand means more vehicles travel along this arterial, which may lead to congestion. For each demand level, the average stop delays of the three types of vehicles decrease with increasing CAVs market penetration rates. This indicates that HVs can benefit more when there is more CAVs in the network. Although this study only optimizes CAV trajectories in a decentralized way, it can also improve the operational performance of HVs and the mixed traffic. In addition, it can be observed that the proposed optimization strategy performs better than the benchmark regarding the average stop delays under all demand levels.

Fig. 12 shows the average lane changing numbers of CAVs, HVs, and the mixed traffic with various market penetration rates under different demand levels. It can be observed that although the lane changing numbers varies under different demand levels, the difference is not significant. It also shows that the optimized trajectories of CAVs can reduce the lane changing numbers under all tested scenarios. However, it can increase the lane changing numbers of HVs when the market penetration rate is 20 %, 25 %, 30 %, and 35 % under all demand levels.

To better evaluate the proposed model, we next analyze the fuel consumption. Many methods for measurement of fuel consumption and emissions have been reported in the literature (e.g., MOVES (Koupal et al., 2002); CMEM (Barth et al., 2000); VT-Micro (Abn et al., 2002)) to estimate instantaneous fuel consumption and emissions based on functions of a vehicle's location, velocity, and acceleration/deceleration at the measured time point (Wang et al., 2020). In this paper, we apply the VT-Micro model to calculate the fuel consumption. The model and related coefficients can be found in the study developed by Ma et al. (2017). Fig. 13 shows the average fuel consumption for each type of vehicle when traveling along this arterial with various market penetration rates under all traffic demand levels. As shown in the table, the optimized trajectory reduced the fuel consumption of CAVs compared with the benchmark trajectories. This is because the proposed strategy can optimize CAV trajectory to reduce the stop-and-go movements traveling along this arterial. Therefore, fuel consumption during starting and stopping can be avoided. Those figures also indicate that the average fuel consumption for HVs and mixed traffic can also be reduced compared with the benchmark. This is because some HVs follow the CAVs to travel along without stops. Then the stop delays of mixed traffic decrease due to the reduced stop delays of CAVs and HVs.

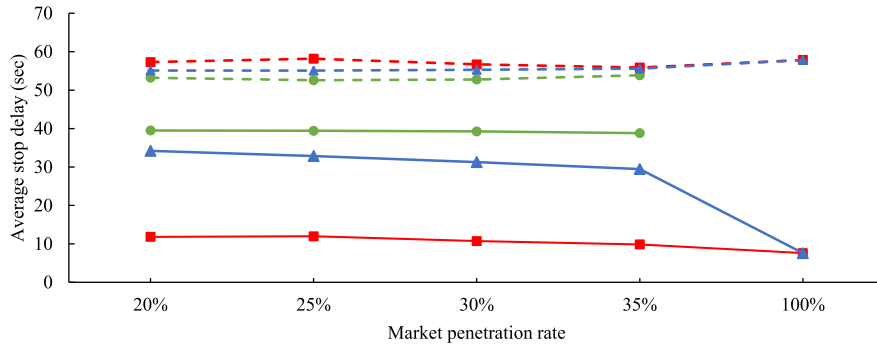
4.2.3. More discussions

We use surrogate safety assessment model (SSAM) to conduct safety analysis. SSAM is a safety assessment software developed by FHWA. SSAM can conduct conflict analysis by processing vehicle trajectory files produces during the simulation. For each vehicle-to-vehicle interaction, SSAM calculates surrogate measures of safety and determines whether that interaction satisfies the criterion to be deemed a conflict (Vasconcelos et al., 2014). Time to collision (TTC) is selected as a threshold to define if a given vehicle is a conflict and it is commonly set to be 1.5 s. Based on the trajectories from simulation and applying SSAM, the rear-end collision is summarized as shown in Fig. 14. We can see that there is no significant difference between the proposed model and the benchmark. Therefore, the safety of the proposed model is reliable.

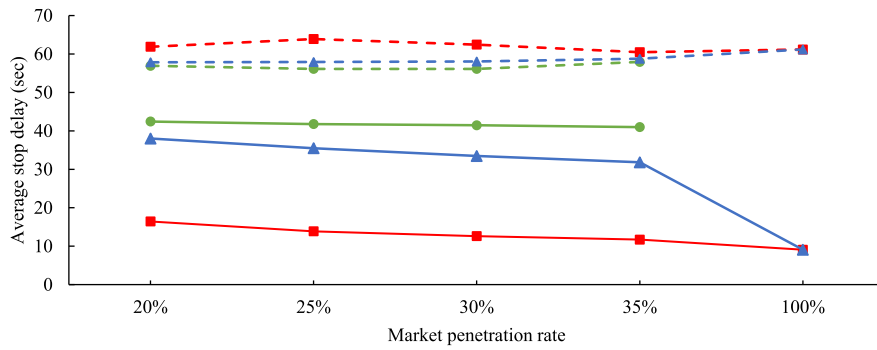
Moreover, this study uses the case of average demand as an example to analyze the average delay, as shown in Table 5. The table indicates that the proposed model will increase the average delay of CAV compared with the benchmark. This is because the goal of this paper is to minimize the stop delay. More specifically, the proposed model will enable some CAV to slow down to travel across the intersection during the green indication, which may result in a higher travel time and thus the increased average delays. In some cases,

Table 4
Average lane-changing numbers with various market penetration rate.

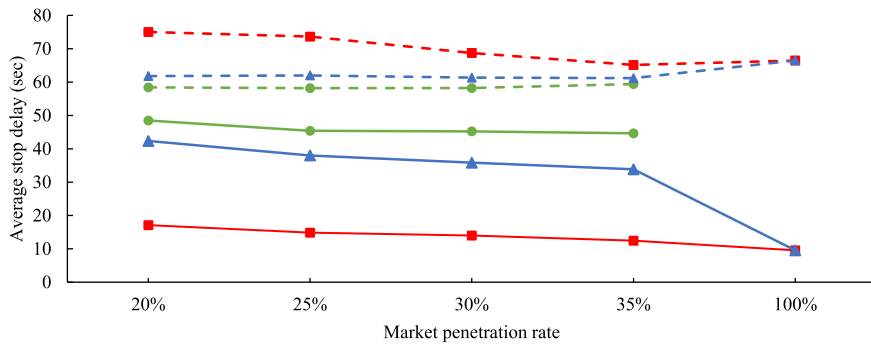
Market penetration rate	Strategies	Vehicle type		
		CAV	HV	Mixed traffic
20 %	Benchmark	2.867	2.896	2.895
	Proposed	2.641	2.911	2.862
25 %	Benchmark	2.874	2.895	2.894
	Proposed	2.796	2.939	2.907
30 %	Benchmark	2.901	2.902	2.094
	Proposed	2.735	3.022	2.937
35 %	Benchmark	2.896	2.892	2.897
	Proposed	2.673	3.053	2.917
100 %	Benchmark	2.891	/	2.891
	Proposed	2.615	/	2.615



(a) low traffic demand



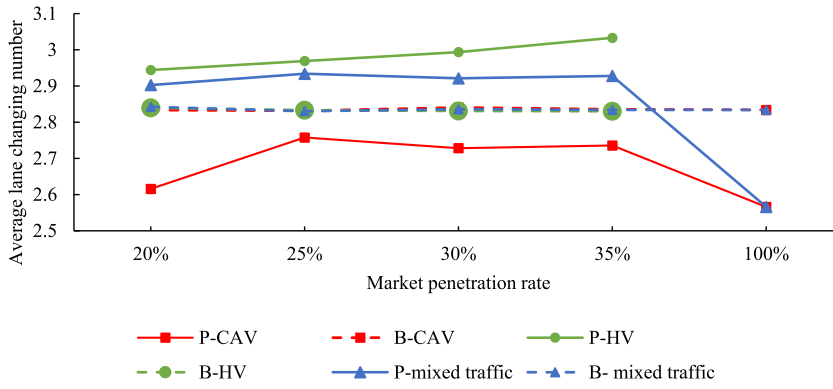
(b) average demand



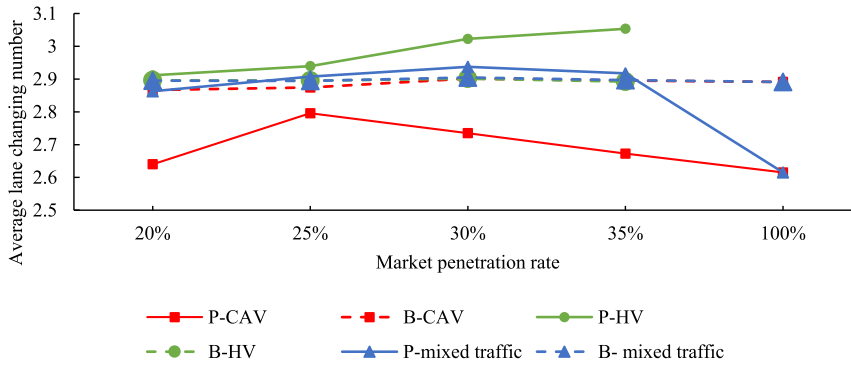
(c) high demand

* P-CAVs and B-CAVs refers to CAVs of proposed model and benchmark, respectively; P-HV, B-HV refer to HVs of proposed model and benchmark; P-mixed traffic and B-mixed traffic refer to mixed traffic of proposed model and benchmark.

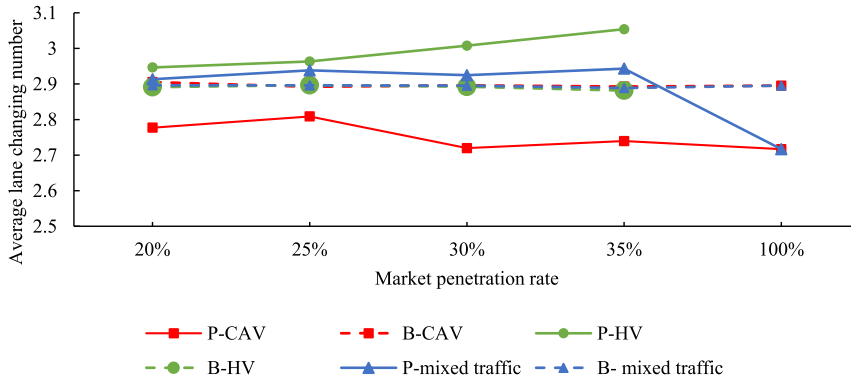
Fig. 11. Average stop delays with various market penetration rate under different demand levels.



(a) low demand



(b) average demand



(c) high demand

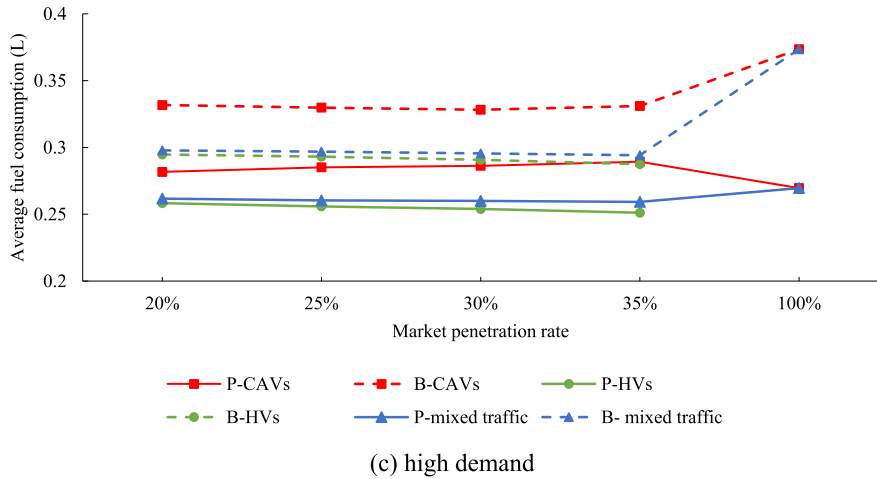
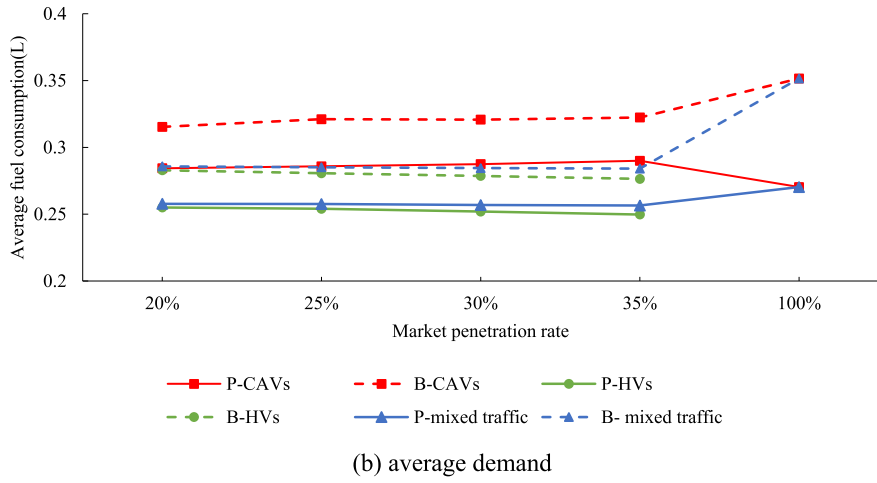
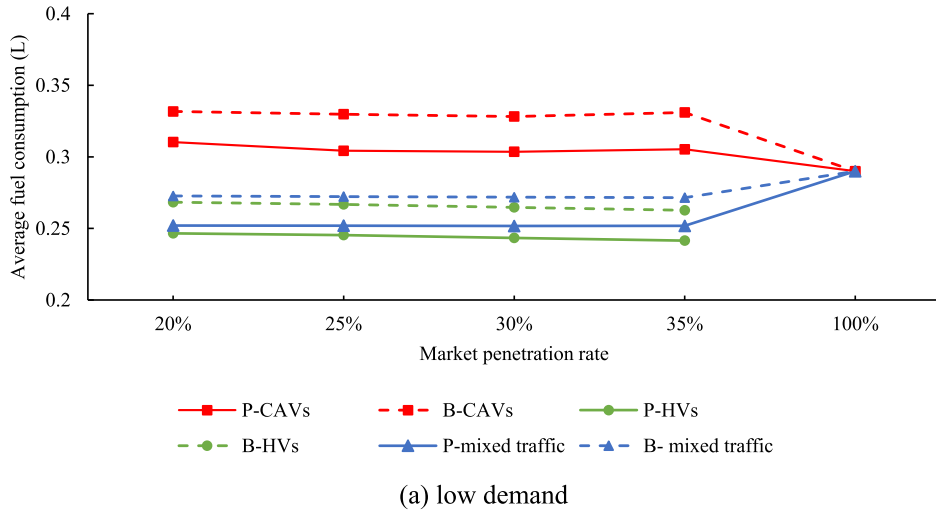
* P-CAVs and B-CAVs refers to CAVs of proposed model and benchmark, respectively; P-HV, B-HV refer to HVs of proposed model and benchmark; P-mixed traffic and B-mixed traffic refer to mixed traffic of proposed model and benchmark.

Fig. 12. Average lane changing number with various market penetration rate under high traffic demand.

there is a trade-off between reducing average vehicle stop delay and average vehicle delay. For example, the average delay of CAV is increases by about 9 s (+10.98 %) compared with the benchmark when the market penetration rate is 35 %. However, the average stop delay is reduced by about 49 s (−80.63 %).

5. Conclusions

CAVs technologies are one of the most promising solutions to the challenges the transportation system undergoing. Trajectory optimization has significant potential to mitigate congestion, reduce energy consumption, improve traffic operation efficiency. This



* P-CAVs and B-CAVs refers to CAVs of proposed model and benchmark, respectively; P-HV, B-HV refer to HVs of proposed model and benchmark; P-mixed traffic and B-mixed traffic refer to mixed traffic of proposed model and benchmark.

Fig. 13. Average lane changing number with various market penetration rate under low traffic demand.

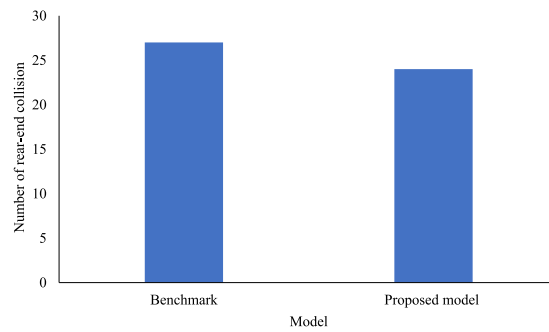


Fig. 14. Rear-end collision of the two different models.

Table 5

Average vehicle delay with various market penetration rate under average demand.

	CAV		HV		All	
	Benchmark	Proposed model	Benchmark	Proposed model	Benchmark	Proposed model
20 %	82.86	86.8	76.38	62.61	77.56	67.36
25 %	85.48	87.36	75.38	62.26	77.72	68.35
30 %	83.76	88.39	75.55	62.69	78.04	70.45
35 %	81.84	90.86	77.49	63.32	78.94	73.14

study proposes a strategy to optimize CAV trajectories along a signalized arterial under the mixed traffic environment consisting of HVs and CAVs. This strategy optimizes CAV trajectories one by one in a decentralized way. Car-following and lane-changing behavior are optimized jointly for each CAV. More specifically, on the basis of signal information and trajectory information of surrounding vehicles, a 2-stage optimization model is developed to optimize CAV trajectories. The stage-1 model is formulated to roughly estimate the minimum travel time with minimum stops of a single CAV traveling along this arterial. Based on this, the stage-2 model is constructed to optimize longitudinal and lateral behavior with minimal delay and lane-changing costs. To solve this model, we applied dynamic programming. Due to time-varying traffic conditions, a rolling horizon scheme is applied to dynamically implement the proposed model.

To evaluate the effectiveness of the proposed strategy, a simulated traffic network is constructed and tested in VISSIM. The proposed model is compared to the benchmark without CAVs trajectory optimization. Results show a sound performance and validate the advantages of the proposed model. As results show, the proposed strategy outperforms the benchmark by reducing the stop delays and lane-changing numbers. Although trajectory optimization is only designed for CAVs, the stop delays of HVs and mixed traffic can also be reduced by the optimized CAV trajectories, especially with a high CAVs market penetration rate. In addition, sensitivity analysis of CAVs market penetration rates and traffic demands all indicate a better performance of the proposed model.

In this study, we assume the signal timing is fixed at each intersection along the arterial. This may limit the improvement the operational performance. Therefore, signal timing optimization and CAV trajectories optimization are supposed to be integrated into a single process to achieve maximum benefits. Moreover, we assume there are no communication delays and CAVs will exactly follow the optimized trajectory, which may not be true in reality. Thus, robust optimization is another research direction. Besides, currently we only considered the through movements of one direction. The mandatory lane changes will be considered in the future research. Last, the microscopic lateral movement will be optimized.

CRedit authorship contribution statement

Qinzheng Wang: Methodology, Investigation, Writing – original draft. **Yaobang Gong:** Data curation, Visualization, Validation. **Xianfeng Yang:** Conceptualization, Supervision, Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

This research is supported by the National Science Foundation grant “CISE #2234292 Collaborative Research: OAC Core: Stochastic Simulation Platform for Assessing Safety Performance of Autonomous Vehicles in Winter Seasons”.

References

- Ahn, K., Rakha, H., Trani, A., Van Aerde, M., 2002. Estimating vehicle fuel consumption and emissions based on instantaneous speed and acceleration levels. *J. Transp. Eng.* 128 (2), 182–190.
- Au, T.C., Stone, P., 2010, July. Motion planning algorithms for autonomous intersection management. In: *Workshops at the Twenty-Fourth AAAI Conference on Artificial Intelligence*.
- Barth, M., An, F., Younglove, T., Scora, G., Levine, C., Ross, M., Wenzel, T., 2000. The development of a comprehensive modal emissions model. NCHRP Web-only document 122, 25–111.
- Carlinio, D., Boyles, S.D. and Stone, P., 2013, October. Auction-based autonomous intersection management. In: *16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013)* (pp. 529–534). IEEE.
- Dresner, K., Stone, P., 2008. A multiagent approach to autonomous intersection management. *J. Artif. Intell. Res.* 31, 591–656.
- Du, Z., HomChaudhuri, B., Pisu, P., 2018. Hierarchical distributed coordination strategy of connected and automated vehicles at multiple intersections. *J. Intell. Transport. Syst.* 22 (2), 144–158.
- Fayazi, S.A., Vahidi, A., 2018. Mixed-integer linear programming for optimal scheduling of autonomous vehicle intersection crossing. *IEEE Trans. Intell. Veh.* 3 (3), 287–299.
- Feng, Y., Yu, C., Liu, H.X., 2018. Spatiotemporal intersection control in a connected and automated vehicle environment. *Transport. Res. Part C: Emerg. Technol.* 89, 364–383.
- Gipps, P.G., 1986. A model for the structure of lane-changing decisions. *Transport. Res. Part B: Methodol.* 20 (5), 403–414.
- Guo, Y., Ma, J., Xiong, C., Li, X., Zhou, F., Hao, W., 2019. Joint optimization of vehicle trajectories and intersection controllers with connected automated vehicles: Combined dynamic programming and shooting heuristic approach. *Transport. Res. Part C: Emerg. Technol.* 98, 54–72.
- He, X., Liu, H.X., Liu, X., 2015. Optimal vehicle speed trajectory on a signalized arterial with consideration of queue. *Transport. Res. Part C: Emerg. Technol.* 61, 106–120.
- HomChaudhuri, B., Vahidi, A., Pisu, P., 2016. Fast model predictive control-based fuel efficient control strategy for a group of connected vehicles in urban road conditions. *IEEE Trans. Control Syst. Technol.* 25 (2), 760–767.
- Huang, X., Peng, H., 2017, May. Speed trajectory planning at signalized intersections using sequential convex optimization. In: *2017 American Control Conference (ACC)* (pp. 2992–2997). IEEE.
- Jiang, H., Hu, J., An, S., Wang, M., Park, B.B., 2017. Eco approaching at an isolated signalized intersection under partially connected and automated vehicles environment. *Transport. Res. Part C: Emerg. Technol.* 79, 290–307.
- Koupal, J., Michaels, H., Cumberworth, M., Bailey, C. and Brzezinski, D., 2002, April. EPA’s plan for MOVES: a comprehensive mobile source emissions model. In: *Proceedings of the 12th CRC On-Road Vehicle Emissions Workshop, San Diego, CA*, pp. 15–17.
- Lee, J., ark, B., 2012. Development and evaluation of a cooperative vehicle intersection control algorithm under the connected vehicles environment. *IEEE Trans. Intell. Transp. Syst.* 3 (1), 81–90.
- Li, X., Peng, F., Ouyang, Y., 2010. Measurement and estimation of traffic oscillation properties. *Transport. Res. Part B: Methodol.* 44 (1), 1–14.
- Li, Z., Chitturi, M.V., Zheng, D., Bill, A.R., Noyce, D.A., 2013. Modeling reservation-based autonomous intersection control in VISSIM. *Transp. Res. Rec.* 2381 (1), 81–90.
- Li, Z., Wu, Q., Yu, H., Chen, C., Zhang, G., Tian, Z.Z., Prevedouros, P.D., 2019. Temporal-spatial dimension extension-based intersection control formulation for connected and autonomous vehicle systems. *Transport. Res. Part C: Emerg. Technol.* 104, 234–248.
- Ma, C., Yu, C., Yang, X., 2021. Trajectory Planning for Connected and Automated Vehicles at Isolated Signalized Intersections under Mixed Traffic Environment. *arXiv preprint arXiv:2102.03518*.
- Ma, J., Li, X., Zhou, F., Hu, J., Park, B.B., 2017. Parsimonious shooting heuristic for trajectory design of connected automated traffic part II: computational issues and optimization. *Transport. Res. Part B: Methodol.* 95, 421–441.
- Mahbub, A.M., Karri, V., Parikh, D., Jade, S. and Malikopoulos, A.A., 2019. A decentralized time-and energy-optimal control framework for connected automated vehicles: From simulation to field test. *arXiv pre*.
- Malikopoulos, A.A., Cassandras, C.G., Zhang, Y.J., 2018. A decentralized energy-optimal control framework for connected automated vehicles at signal-free intersections. *Automatica* 93, 244–256.
- Mirheli, A., Tajalli, M., Hajibabai, L., Hajbabaie, A., 2019. A consensus-based distributed trajectory control in a signal-free intersection. *Transport. Res. Part C: Emerg. Technol.* 100, 161–176.
- Mirheli, A., Tajalli, M., Hajibabai, L., Hajbabaie, A., 2019. A consensus-based distributed trajectory control in a signal-free intersection. *Transportation research part C: emerging technologies* 100, 161–176.
- Pourmehrab, M., Elefteriadou, L., Ranka, S., Martin-Gasulla, M., 2019. Optimizing signalized intersections performance under conventional and automated vehicles traffic. *IEEE Trans. Intell. Transp. Syst.* 21 (7), 2864–2873.
- Rafter, C.B., Anvari, B., Box, S., Cherrett, T., 2020. Augmenting traffic signal control systems for urban road networks with connected vehicles. *IEEE Trans. Intell. Transp. Syst.* 21 (4), 1728–1740.
- Vasconcelos, L., Silva, A.B., Seco, Á.M., Fernandes, P., Coelho, M.C., 2014. Turboroundabouts: multicriterion assessment of intersection capacity, safety, and emissions. *Transp. Res. Rec.* 2402 (1), 28–37.
- Volpe, J.A., 2008. Vehicle-infrastructure integration (VII) initiative benefit-cost analysis version 2.3 (draft). National Transportation Systems Center, FHWA.
- Wan, N., Vahidi, A., Luckow, A., 2016. Optimal speed advisory for connected vehicles in arterial roads and the impact on mixed traffic. *Transport. Res. Part C: Emerg. Technol.* 69, 548–563.
- Wang, Q., Yang, X., Huang, Z., Yuan, Y., 2020. Multi-vehicle trajectory design during cooperative adaptive cruise control platoon formation. *Transp. Res. Rec.* 2674 (4), 30–41.
- Wang, Q., Yuan, Y., Yang, X.T., Huang, Z., 2021. Adaptive and multi-path progression signal control under connected vehicle environment. *Transport. Res. Part C: Emerg. Technol.* 124, 102965.
- Wang, Z., Wu, G., Hao, P., Barth, M.J., 2018. Cluster-wise cooperative eco-approach and departure application for connected and automated vehicles along signalized arterials. *IEEE Trans. Intell. Veh.* 3 (4), 404–413.
- Wiedemann, R., 1974. *Simulation des Strassenverkehrsflusses*.
- Wei, Y., Avci, C., Liu, J., Belezamo, B., Aydin, N., Li, P.T., Zhou, X., 2017. Dynamic programming-based multi-vehicle longitudinal trajectory optimization with simplified car following models. *Transport. Res. Part B: Methodol.* 106, 102–129.
- Xu, B., Ban, X.J., Bian, Y., Li, W., Wang, J., Li, S.E., Li, K., 2018. Cooperative method of traffic signal optimization and speed control of connected vehicles at isolated intersections. *IEEE Trans. Intell. Transp. Syst.* 20 (4), 1390–1403.
- Yang, H., Rakha, H., Ala, M.V., 2016a. Eco-cooperative adaptive cruise control at signalized intersections considering queue effects. *IEEE Trans. Intell. Transp. Syst.* 18 (6), 1575–1585.

- Yang, K., Guler, S.I., Menendez, M., 2016b. Isolated intersection control for various levels of vehicle technology: Conventional, connected, and automated vehicles. *Transport. Res. Part C: Emerg. Technol.* 72, 109–129.
- Yao, H., Li, X., 2020. Decentralized control of connected automated vehicle trajectories in mixed traffic at an isolated signalized intersection. *Transport. Res. Part C: Emerg. Technol.* 121, 102846.
- Yu, C., Feng, F., Liu, H.X., Ma, W., Yang, X., 2018. Integrated optimization of traffic signals and vehicle trajectories at isolated urban intersections. *Transportation Research Part B: Methodological* 112, 89–112.
- Yu, C., Feng, Y., Liu, H.X., Ma, W., Yang, X., 2019. Corridor level cooperative trajectory optimization with connected and automated vehicles. *Transport. Res. Part C: Emerg. Technol.* 105, 405–421.
- Zhang, K., Zhang, D., de La Fortelle, A., Wu, X., Gregoire, J., 2015. State-driven priority scheduling mechanisms for driverless vehicles approaching intersections. *IEEE Trans. Intell. Transp. Syst.* 16 (5), 2487–2500.
- Zhang, Y.J., Malikopoulos, A.A., Cassandras, C.G., 2016, July. Optimal control and coordination of connected and automated vehicles at urban traffic intersections. In: *2016 American Control Conference (ACC)* (pp. 6227–6232). IEEE.
- 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 signalized intersection. *Transport. Res. Part C: Emerg. Technol.* 95, 802–821.
- Zhou, F., Li, X., Ma, J., 2017. Parsimonious shooting heuristic for trajectory design of connected automated traffic part I: Theoretical analysis with generalized time geography. *Transport. Res. Part B: Methodol.* 95, 394–420.
- Zohdy, I.H., Rakha, H.A., 2016. Intersection management via vehicle connectivity: The intersection cooperative adaptive cruise control system concept. *J. Intell. Transport. Syst.* 20 (1), 17–32.