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The Penetration Effect of Connected Automated Vehicles in Urban Traffic: An Energy Impact Study

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Abstract— **Earlier work has established a decentralized framework of optimally controlling connected and automated vehicles (CAVs) crossing an urban intersection without using explicit traffic signaling. The proposed solution is capable of minimizing energy consumption subject to a throughput maximization requirement. In this paper, we address the problem of optimally controlling CAVs under mixed traffic conditions where both CAVs and human-driven vehicles (non-CAVs) travel on the roads, so as to minimize energy consumption while guaranteeing safety constraints. The impact of CAVs on overall energy consumption is also investigated under different traffic scenarios. The benefit from CAV penetration (i.e., the fraction of CAVs relative to all vehicles) is validated through simulation in MATLAB and VISSIM. The results indicate that the energy efficiency improvement becomes more significant as the CAV penetration rate increases, while the significance diminishes as the traffic becomes heavier.**

I. INTRODUCTION

To date, traffic light signaling is the prevailing method used for controlling the traffic flow at urban intersections. Exploiting data-driven control and optimization approaches, recent research (e.g., see [1]) has enabled the adaptive adjustment of traffic light cycles, leading to reduced congestion. However, aside from the obvious infrastructure cost, urban traffic lights can lead to more rear-end collisions and reduced safety. These issues have motivated research efforts on new approaches for signal-free intersection traffic control.

Connected and Automated Vehicles (CAVs) possess the potential to change the transportation landscape by enabling users to better monitor transportation network conditions and to improve traffic flow in terms of reducing energy consumption, travel delays, accidents and emissions. One of the very early efforts was proposed in [2], where an optimal linear feedback regulator is designed to control a string of vehicles. Dresner and Stone [3] proposed a reservation-based scheme for autonomous intersection management, whereby a centralized controller coordinates the vehicle crossing sequence based on the request received from the vehicles. Numerous efforts based on reservation schemes have been reported in the literature [4]–[6]. Reducing the travel delay and increasing the throughput of an intersection is one desired goal to be achieved. Relevant efforts include [7]–[10] which aim at minimizing the vehicle travel time under collision-avoidance constraints. Lee and Park [11] focused on minimizing the overlap between vehicle positions. Miculescu and Karaman [12] used a polling-system to model the intersection. A detailed discussion can be found in [13].

Our earlier work [14] has established a decentralized optimal control framework for coordinating online a continuous flow of CAVs crossing an urban intersection without using explicit traffic signaling. For each CAV, an energy minimization optimal control problem is formulated where the time to cross the intersection is first determined through a throughput maximization problem. We also established conditions under which feasible solutions to the optimal control problem exist.

The benefits of CAV coordination and control on energy consumption have been established and quantified in recent literature [15]–[18]. However, the integration of CAVs with conventional vehicles faces several challenges before their penetration rate (i.e., the fraction of CAVs relative to all vehicles in a transportation system) becomes significant. Thus, a critical question is that of determining the penetration effect of CAVs under mixed traffic conditions. Under such conditions, it is necessary to design control algorithms for CAVs and coordination policies that can accommodate both CAVs and conventional human-driven vehicles. Dresner and Stone [19] proposed a light model that can control the physical traffic lights as well as implementing a reservation-based control algorithm for autonomous vehicles while ensuring safety. Other efforts include using information from CAVs to better adapt the traffic light in a mixed traffic scenario (e.g., see [20]). In this paper, we address the problem of optimally controlling the CAVs crossing an urban intersection in a mixed traffic scenario where both CAVs and non-CAVs (conventional human-driven vehicles) travel on the roads. A decentralized optimal control framework is presented whose solution yields the optimal acceleration/deceleration so as to minimize the energy consumption subject to a throughput maximizing requirement, while taking the interaction between CAVs and non-CAVs into consideration.

The structure of the paper is as follows. In Section II, we review the model in [14] and its generalization in [21]. In Section III, we formulate the optimal control problem for each CAV under mixed traffic conditions and present the analytical solutions. In Section IV, we introduce the non-CAV model and the approaches for collision avoidance among CAVs and non-CAVs to complete the establishment of the mixed traffic scenario. In Section V, we investigate the impact of CAV penetration on energy economy under different traffic scenarios. We offer concluding remarks in Section VI.

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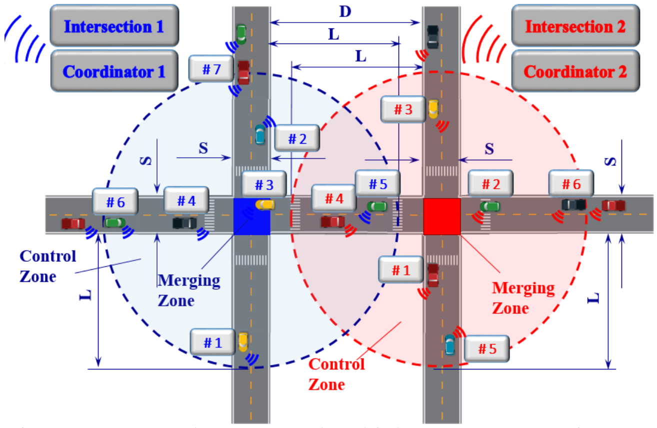

Fig. 1: Connected Automated Vehicles (CAVs) crossing two adjacent intersections.

II. The Model

We briefly review the model introduced in [14] where there are two intersections, 1 and 2, located within a distance D (Fig. 1). The region at the center of each intersection, called *Merging Zone* (MZ), is the area of potential lateral CAV collision. Although it is not restrictive, this is taken to be a square of side S. Each intersection has a *Control Zone* (CZ) and a coordinator that can communicate with the CAVs traveling within it. The distance between the entry of the CZ and the entry of the MZ is $L > S$, and it is assumed to be the same for all entry points to a given CZ.

Let $N_z(t) \in \mathbb{N}$ be the cumulative number of CAVs which have entered the CZ of intersection z at t and formed a queue $\mathcal{N}_z(t) = \{1, \ldots, N_z(t)\}$ which designates the order in which these vehicles will be entering the MZ. The way the queue is formed is not restrictive. When a CAV reaches the CZ of intersection z, the coordinator assigns it an integer value $i = N_z(t) + 1$. If two or more CAVs enter a CZ at the same time, then the corresponding coordinator selects randomly the first one to be assigned the value $N_z(t) + 1$. In the region between the exit point of a MZ and the entry point of the subsequent CZ, the CAVs are assumed to cruise with the speed they had when they exited that MZ.

For simplicity, we assume that each CAV is governed by second order dynamics:

$$\dot{p}_i(t) = v_i(t), \;\; p_i(t_i^0) = 0; \;\; \dot{v}_i(t) = u_i(t), \; v_i(t_i^0) \text{ given} \quad (1)$$

where $p_i(t)$, $v_i(t)$, and $u_i(t)$ denote the position (i.e., travel distance since the entry of the CZ), speed and acceleration/deceleration (i.e., control input) of each CAV i. These dynamics are in force over an interval $[t_i^0, t_i^f]$, where t_i^0 and t_i^f are the times that CAV i enters the CZ and exits the MZ of intersection z respectively.

To ensure that the control input and vehicle speed are within a given admissible range, the following constraints are imposed:

$$\begin{aligned} &u_{i,min} \leq u_i(t) \leq u_{i,max}, \quad \text{and} \\ &\quad 0 \leq v_{min} \leq v_i(t) \leq v_{max}, \quad \forall t \in [t_i^0, t_i^m], \end{aligned} \quad (2)$$

where t_i^m is the time that CAV i enters the MZ.

Definition 1: Depending on its physical location inside the CZ, CAV $j \in \mathcal{N}_z(t), j \neq i$ belongs to only one of the following four subsets of $\mathcal{N}_z(t)$ with respect to CAV i: 1) $\mathcal{R}_i^z(t)$ contains all CAVs traveling on the same road as i and towards the same direction but on different lanes, 2) $\mathcal{L}_i^z(t)$ contains all CAVs traveling on the same road and lane as vehicle i (e.g., $\mathcal{L}_6^1(t)$ contains CAV #4 in Fig. 1), 3) $\mathcal{C}_i^z(t)$ contains all CAVs traveling on different roads from i and having destinations that can cause collision at the MZ (e.g., $\mathcal{C}_7^1(t)$ contains CAV #6 in Fig. 1), and 4) $\mathcal{O}_i^z(t)$ contains all CAVs traveling on the same road as i and opposite destinations that cannot, however, cause collision at the MZ (e.g., $\mathcal{O}_4^1(t)$ contains CAV #3 in Fig. 1).

To ensure the absence of any rear-end collision throughout the CZ, we impose the *rear-end safety constraint*:

$$s_i(t) = p_k(t) - p_i(t) \geq \delta, \;\; \forall t \in [t_i^0, t_i^m], \;\; k \in \mathcal{L}_i^z(t) \quad (3)$$

where k is the CAV physically ahead of i on the same lane, $s_i(t)$ is the inter-vehicle distance between i and k, and δ is the *minimal safe following distance* allowable.

A lateral collision involving CAV i may occur only if some CAV $j \neq i$ belongs to $\mathcal{C}_i^z(t)$. This leads to the following definition:

Definition 2: For each CAV $i \in \mathcal{N}_z(t)$, we define the set Γ_i that includes all time instants when a lateral collision involving CAV i is possible: $\Gamma_i \triangleq \Big\{t \mid t \in [t_i^m, t_i^f]\Big\}$.

Consequently, to avoid a lateral collision for any two vehicles $i, j \in \mathcal{N}_z(t)$ on different roads, the following constraint should hold

$$\Gamma_i \cap \Gamma_j = \varnothing, \quad \forall t \in [t_i^m, t_i^f], \;\; j \in \mathcal{C}_i^z(t). \quad (4)$$

As part of safety considerations, we impose the following assumption (which may be relaxed if necessary):

Assumption 1: For CAV i, none of the constraints in (2)-(3) is active at t_i^0.

Assumption 2: The speed of the CAVs inside the MZ is constant, i.e., $v_i(t) = v_i(t_i^m) = v_i(t_i^f)$, $\forall t \in [t_i^m, t_i^f]$. This implies that $t_i^f = t_i^m + \frac{S}{v_i(t_i^m)}$.

Assumption 3: Each CAV i has proximity sensors and can measure local information without errors or delays.

The objective of each CAV is to derive an optimal acceleration/deceleration profile, in terms of minimizing energy consumption, inside the CZ while avoiding congestion between the two intersections. Since the coordinator is not involved in any decision making process on the vehicle control, we can formulate $N_1(t)$ and $N_2(t)$ decentralized tractable problems for intersection 1 and 2 respectively that can be solved online. The terminal times for CAVs entering the MZ can be first obtained as the solutions to a throughput maximization problem formulated in [21] subject to rear-end and lateral collision avoidance constraints inside the MZ (details can be found in [22]). The conditions under which the rear-end safety constraint in (3) does not become active inside the CZ are provided in [23].

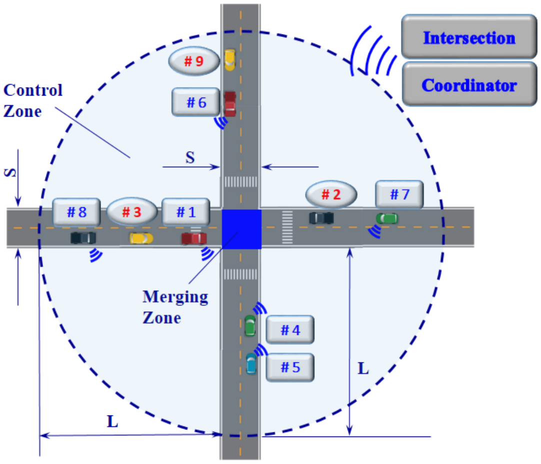

Fig. 2: Connected Automated Vehicles (blue labels) and non-CAVs (red labels) crossing an urban intersection.

III. Optimal Control of CAVs in Mixed Traffic

We consider the mixed traffic scenario (Fig. 2) where both CAVs and non-CAVs travel on the roads. The first major issue to be addressed is modeling the interaction between CAVs and non-CAVs where we assume that the latter do not possess the capability to communicate with other vehicles.

Regarding a CAV, there are two modes that it can be in: (i) *Free Driving* (FD mode) when it is not constrained by a non-CAV that precedes it. (ii) *Adaptive Following* (AF mode) when it follows a preceding non-CAV while adaptively maintaining a safe following distance from it. CAVs switch from the FD mode to the AF mode as soon as the inter-vehicle distance falls below a certain threshold.

A. Optimal Control for Free Driving (FD) Mode

In this mode, the objective of each CAV is to derive an optimal acceleration/deceleration profile, in terms of minimizing energy consumption, inside the CZ, that is,

$$\begin{aligned} &\min_{u_i \in U_i} \frac{1}{2} \int_{t_i^0}^{t_i^m} K_i \cdot u_i^2(t)\, dt \\ &\text{subject to : (1), (2)}, t_i^m,\ p_i(t_i^0) = 0,\ p_i(t_i^m) = L, \\ &\text{given } t_i^0,\ v_i(t_i^0), \end{aligned} \tag{5}$$

where K_i is a factor to capture CAV diversity (for simplicity, $K_i = 1$ in the remainder of this paper). Note that this formulation does not include the rear-end safety constraint in the CZ in (3); we will return to this issue in what follows. On the other hand, the rear-end and lateral collision avoidance inside the MZ can be implicitly ensured by t_i^m.

An analytical solution of problem (5) may be obtained through a Hamiltonian analysis found in [21]. Assuming that all constraints are satisfied upon entering the CZ and that they remain inactive throughout $[t_i^0, t_i^m]$, the optimal control input (acceleration/deceleration) over $t \in [t_i^0, t_i^m]$ is given by

$$u_i^*(t) = a_i t + b_i \tag{6}$$

where a_i and b_i are constants of integration. Using (6) in the CAV dynamics (1), the optimal speed and position are obtained: $v_i^*(t) = \frac{1}{2}a_i t^2 + b_i t + c_i$, $p_i^*(t) = \frac{1}{6}a_i t^3 + \frac{1}{2}b_i t^2 + c_i t + d_i$, where c_i and d_i are constants of integration. The coefficients a_i, b_i, c_i, d_i can be obtained given initial and terminal conditions.

Note that the analytical solution (6) is valid while none of the constraints becomes active for $t \in [t_i^0, t_i^m]$. Otherwise, the optimal solution should be modified considering the constraints, as discussed in [21]. While the constraint (3) is not included in (5), conditions under which the CAV is able to maintain feasibility in terms of satisfying (3) over $t \in [t_i^0, t_i^m]$ are derived in [23] along with an explicit mechanism to enforce them prior to entering the CZ.

B. Optimal Control for Adaptive Following (AF) Mode

When the preceding vehicle for CAV i is also a CAV, the feasibility of the optimal solution (6)) can be enforced through an appropriately designed *Feasibility Enforcement Zone* that precedes the CZ as described in [23]. Otherwise, when the inter-vehicle distance $s_i(t)$ between CAV i and the preceding vehicle k falls below a certain threshold δ_f at t_i^1, CAV i transitions from the FD to the AF mode (Fig. 3(a)). Since CAV i cannot communicate with the preceding non-CAV, it simply assumes a constant speed for the non-CAV.

In this mode, the objective of each CAV is to derive an optimal acceleration/deceleration profile so as to minimize energy consumption, while maintaining the *minimum safe following distance* δ with the preceding non-CAV, that is,

$$\begin{aligned} &\min_{u_i \in U_i} \frac{1}{2} \int_{t_i^1}^{t_i^m} [w_u \cdot u_i^2(t) + w_s \cdot (s_i(t) - \delta)^2]\, dt \\ &\text{subject to : (1), (2)}, t_i^m,\ p_i(t_i^m) = L, \\ &\text{and given } t_i^1,\ v_i(t_i^1), p_i(t_i^1), \end{aligned} \tag{7}$$

where w_u and w_s are weights applied to the objective function, which allow trading off energy consumption minimization against maintaining the safe following distance.

The analytical solution of problem (7) may be obtained through a Hamiltonian analysis similar to that in [14] and [21]. Assuming that all constraints are satisfied at t_i^1 and that they remain inactive throughout $[t_i^1, t_i^m]$, the optimal control input (acceleration/deceleration) over $t \in [t_i^1, t_i^m]$ can be determined as follows. Defining $w = \frac{\sqrt{4w_u \cdot w_s}}{2w_u}$ and $\alpha = \sqrt{\frac{w}{2}}$, the optimal control can be obtained as

$$\begin{aligned} u_i^*(t) = &- 2a_i\alpha^2 e^{\alpha t} sin(\alpha t) + 2b_i\alpha^2 e^{-\alpha t} sin(\alpha t) \\ &+ 2c_i\alpha^2 e^{\alpha t} cos(\alpha t) - 2d_i\alpha^2 e^{-\alpha t} cos(\alpha t). \end{aligned} \tag{8}$$

The optimal speed and position can be obtained according to (1). The constants of integration a_i, b_i, c_i and d_i can be obtained given initial and terminal conditions.

C. Terminal Conditions

Under mixed traffic conditions, the recursive terminal time structure derived in [21] can no longer be applied since non-CAVs are not controlled to follow the order imposed by the queueing structure. To determine the terminal conditions for CAV i, there are two different cases to consider: (i) vehicle $i-1$ is a CAV, and (ii) vehicle $i-1$ is a non-CAV. If vehicle $i-1$ is a CAV, then the terminal time for CAV i can

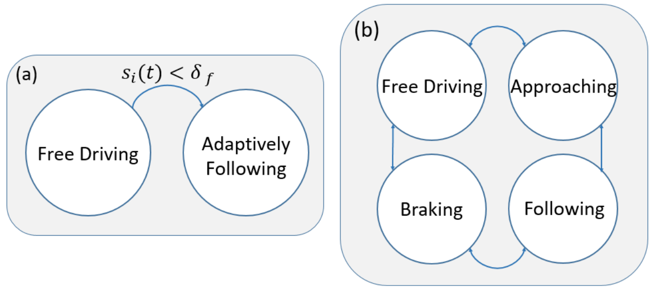

Fig. 3: (a) Modeling approach for CAVs; (b) The Wiedemann model for non-CAVs.

be recursively determined through CAV $i-1$ as in [21]; if vehicle $i-1$ happens to be a non-CAV, then the terminal time for CAV i is determined by estimating the terminal time of vehicle $i-1$. In particular, at time t_i^0, vehicle $i-1$ is at position $p_{i-1}(t_i^0)$ with speed $v_{i-1}(t_i^0)$, which can be measured by CAV i through on-board sensors or through the coordinator. As CAV i cannot communicate with non-CAV $i-1$, it simply assumes a constant speed for $i-1$, i.e., $v_{i-1}(t) = v_{i-1}(t_i^0)$ for $t \in [t_i^0, t_i^m]$. Denoting the estimated terminal time for vehicle $i-1$ as $\hat{t}_{i-1}^m$, we have

$$\hat{t}_{i-1}^m = t_i^0 + \frac{L - p_{i-1}(t_i^0)}{v_{i-1}(t_i^0)}, \tag{9}$$

based on which, CAV i can determine its own terminal time for entering the MZ. Note that the estimation may need re-evaluation in the case that non-CAV $i-1$ changes speed.

D. Simulation Example

The proposed optimal control framework for CAVs is illustrated through the following simulation example, where the length of the CZ is $L = 400$m. Vehicle #1 is assumed to be a non-CAV entering the CZ at $t_1^0 = 0$ and cruising at its initial speed $v_1^0 = 10$m/s. CAV #2 enters the same lane as vehicle #1 at $t_2^0 = 2$s with an initial speed $v_2^0 = 15$m/s. The *minimum safe following distance* is set to $\delta = 10$m. With the weights w_u and w_s both set to be 1, the optimal speed trajectory of CAV #2 (i.e., $v_2(t)$) and the inter-vehicle distance between vehicle #1 and CAV #2 (i.e., $s_2(t)$) with and without the AF mode are shown in Fig. 4.

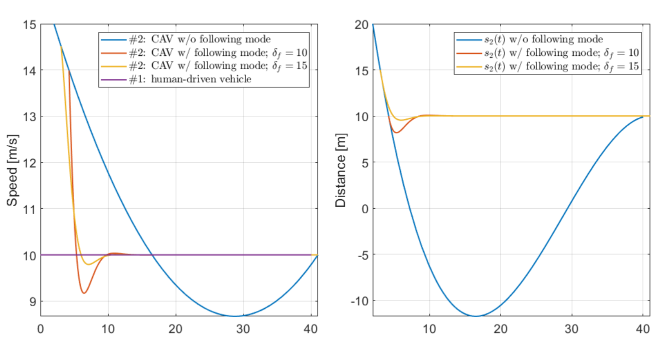

Fig. 4: Speed $v_i(t)$ and inter-vehicle distance $s_2(t)$ trajectories w/ and w/o the optimal control for adaptively following.

Without a transition to the AF mode, CAV #2 violates the rear-end collision constraint (blue curve in Fig. 4) and the distance $s_2(t)$ falls below $\delta = 10$m for $t > 4.22$s. With the AF mode in force (red and yellow curves), when the distance reaches the threshold, i.e., $s_2(t) = \delta_f$, CAV #2 first decelerates so as to reach a much lower speed than vehicle #1, and then seeks to keep the distance as close to $\delta = 10$m as possible. Note that the process of adaptively following implicitly forces CAV #2 to maintain the same speed as vehicle #1.

For the scenarios using the AF mode, the threshold for entering this mode is set to either $\delta_f = 10$m (red curve) or $\delta_f = 15$m (yellow curve). The energy consumption, given by a polynomial function of speed and acceleration, is obtained as 0.0156 and 0.0143, respectively. The energy cost reduction results from the fact that CAV #2 enters the AF mode earlier given $\delta_f = 15$m, hence, it does not need to decelerate as hard as in the case with $\delta_f = 10$m. The approaching process becomes smoother, which leads to lower energy consumption.

IV. Modeling Methodology for non-CAVs

There are two major issues that need to be addressed in terms of modeling non-CAVs: (i) modeling the car-following behavior, and (ii) designing a collision avoidance approach inside the MZ without explicit traffic signaling.

A. The Wiedemann Approach

In this paper, we apply the Wiedemann model [24], the default approach adopted by VISSIM, the transportation system simulator, to model car-following behavior. The basic idea of the Wiedemann model is that a non-CAV can be in one of the following four driving modes: (i) *Free driving*: No observable influence by any preceding vehicle. (ii) *Approaching*: The driver adapts his/her own speed to the speed of a preceding vehicle. (iii) *Following*: The driver follows the preceding vehicle while trying to (approximately) maintain a safe distance from the vehicle being followed. (iv) *Braking*: The driver applies the brake to decelerate if the distance from the preceding vehicle falls below the desired safety level. The modeling approach for non-CAVs is summarized in Fig. 3(b). For each mode, there are several associated parameters that model specific car-following behavior.

B. Conflict Areas

As non-CAVs may not follow the prescribed order in the queueing structure, lateral collisions may occur inside the MZ when no traffic lights are present. There are several ways used in VISSIM to model non-signalized intersections for non-CAVs, by defining *Priority Rules*, *Conflict Areas*, and *Stop Sign Control*. Among these techniques, *Conflict Areas* provide modeling ease and more intelligent behavior and will be adopted in the sequel to ensure the absence of lateral collisions in the MZ.

If a CAV enters the MZ at the designated terminal time t_i^m while a non-CAV is present inside the MZ, the CAV simply forgoes the constant speed assumption (*Assumption 2*) and follows the *Conflict Areas* rule so as to avoid lateral collision. As shown in Fig. 5, there are three options for defining

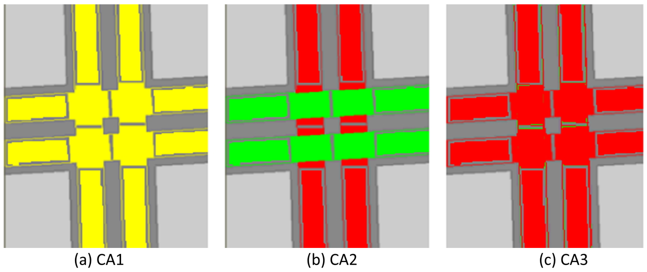

Fig. 5: Different states of conflict areas.

conflict areas. Fig. 5(a) indicates a passive conflict area, i.e., all vehicles are uncontrolled in terms of lateral collision avoidance (CA1). Fig. 5(b) shows a partially controlled conflict area, where the vehicles on the main road (green) are uncontrolled because they have priority to cross the MZ, while vehicles on the minor road (red) are controlled because they have to yield (CA2). Fig. 5(c) shows a fully controlled conflict area. As there is no right of way, vehicles on both roads are under control (CA3).

V. Energy Impact of CAV Penetration Under Different Traffic Scenarios

The energy impact study is carried out through a combination of MATLAB and VISSIM simulations. We consider a group of CAVs and non-CAVs crossing a single urban intersection with the same settings in Sec. III-D. For each direction, only one lane is considered. The threshold for entering the AF mode is $\delta_f = 10$m. The weights w_u and w_s in (7) are both set to 1. The vehicle arrivals are assumed to be given by a Poisson process and the initial speeds are uniformly distributed over $[10.9, 11.1]$m/s.

A. Energy Impact of CAV Penetration

We first compare the energy impact over different CAV penetration rates. Note that with 100% CAV penetration, all CAVs proceed according to the optimal trajectories determined in Sec. III and reach the MZ at the designated terminal times. However, for cases with less than 100% CAV penetration, we adopt the non-signalized collision avoidance rule (i.e., *Conflict Areas*) in mixed traffic, as non-CAVs may not follow the prescribed order in the queueing structure specified by the coordinator. The energy consumption with respect to different CAV penetration rates given the traffic flow rate set to $\lambda = 700$veh/(hour·lane) is shown in Fig. 6. It can be seen that as the CAV penetration rate increases, the energy consumption decreases, which validates the efficiency of CAV penetration in terms of improving energy economy.

Observe in Fig. 6 that with no CAVs (0% penetration rate), the *Conflict Areas* cannot outperform the traffic light control case (indicated by TLC); however, with as little as 10% CAV penetration rate, TLC is outperformed. This leads to the conclusion that approximately 10% of vehicles should be CAVs before energy consumption performance can exceed that of TLC. However, this value clearly depends on traffic flow rates, which will be further discussed in Sec. V-B.

An additional important observation is that energy performance is not always monotonically increasing with the penetration rate value. In Fig. 6, the energy consumption

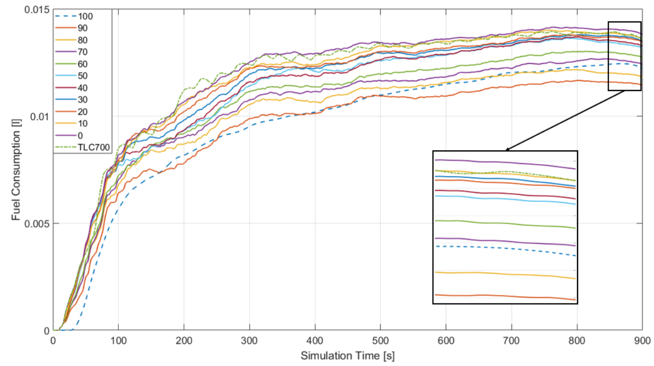

Fig. 6: Energy consumption per second with respect to different CAV penetration rates given traffic flow rate set to $\lambda = 700$veh/(hour·lane).

under 100% CAV penetration is worse than that with 90% and even 80% penetration rates. This is attributed to the overly conservative nature of our approach for determining the terminal time sequence, specifically the fact that only one vehicle is allowed inside the MZ at any time for vehicles traveling from different directions (4). On the other hand, the collision avoidance approach adopted under mixed traffic conditions (i.e., *Conflict Areas*) makes better use of the MZ by allowing vehicles to share it at the same time. Such more efficient MZ utilization reduces unnecessary travel delays.

B. Energy Impact of CAV Penetration Under Different Traffic Flow Rates

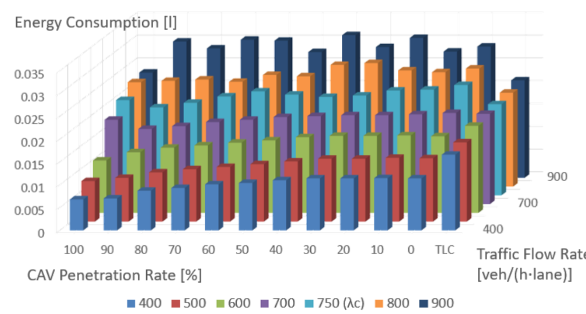

Fig. 7: Average energy consumption with respect to different traffic flow rates and CAV penetration rates.

To explore the energy impact of CAV penetration with different traffic flow rates, a comparison is presented in Fig. 7 that shows the energy consumption with respect to both different CAV penetration rates and traffic flow rates. To achieve the best performance, the traffic flow rate is set approximately under $\lambda_c = 750$veh/(h·lane). Observe that with lower traffic flow rates, that is, when the intersection is under-saturated (i.e., $\lambda < \lambda_c$), the benefit obtained from CAV penetration is more significant. Even the case with no CAVs can outperform the TLC case. With higher traffic flow rates, that is, when the degree of saturation of the intersection is near or over 1 (i.e., $\lambda > \lambda_c$), energy consumption can hardly gain any benefit from CAV penetration. This is consistent with our expectation: when the traffic is light, the red lights prevent some vehicles from crossing the intersection even if there is no other traffic that could generate collision inside the MZ; when the traffic is heavy, both CAVs and non-CAVs need to slow down or even stop to yield when they approach the MZ without traffic signaling and accelerate after they leave the intersection, which may consume more energy compared to the TLC case, where some vehicles do not need to stop during the green light phase.

The corresponding average travel times are shown in Fig. 8. Observe that before the traffic flow rate reaches the critical flow rate (i.e., $\lambda < \lambda_c$), the TLC cases are slightly outperformed. This may be due to the fact that the red lights prevent some vehicles from crossing the MZ even if there is no other traffic that could generate collision, while the non-signalized coordination policy makes better use of the MZ by allowing more vehicles sharing the MZ at the same time and hence reduces travel delay. When the traffic is heavy (i.e., $\lambda > \lambda_c$), almost all the vehicles have to slow down or even stop to yield when approaching the MZ without traffic signaling, which greatly increases the travel time.

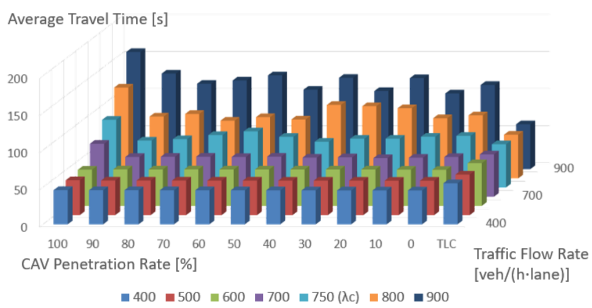

Fig. 8: Average travel time with respect to different traffic flow rates and CAV penetration rates.

VI. Concluding Remarks

Earlier work [14] and [21] have established a decentralized framework for optimally controlling CAVs crossing urban intersections. In this paper, we extended the solution of this problem to accommodate non-CAVs by formulating another optimal control problem to adaptively follow the preceding non-CAV. In addition, we investigate the energy impact of CAV penetration under different traffic scenarios. The simulation results validate the effectiveness of CAV penetration, and as the CAV penetration rate increases, the benefit becomes more significant.

Ongoing research is exploring energy impact under different modeling approaches for, e.g., vehicle behavior and collision avoidance inside the MZ (see [22]). We are also considering turns (see [25]) and the potential to further maximize the traffic throughput by introducing a dynamic resequencing process. Future research should extend the current framework to a grid of intersections.

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