Mixed-Traffic Intersection Management Utilizing Connected and Autonomous Vehicles as Traffic Regulators

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ABSTRACT

Connected and autonomous vehicles (CAVs) can realize many revolutionary applications, but it is expected to have mixed-traffic including CAVs and human-driving vehicles (HVs) together for decades. In this paper, we target the problem of mixed-traffic intersection management and schedule CAVs to control the subsequent HVs. We develop a dynamic programming approach and a mixed integer linear programming (MILP) formulation to optimally solve the problems with the corresponding intersection models. We then propose an MILP-based approach which is more efficient and real-time-applicable than solving the optimal MILP formulation, while keeping good solution quality as well as outperforming the first-come-first-served (FCFS) approach. Experimental results and SUMO simulation indicate that controlling CAVs by our approaches is effective to regulate mixed-traffic even if the CAV penetration rate is low, which brings incentive to early adoption of CAVs.

CCS CONCEPTS

• **Computer systems organization → Embedded and cyber-physical systems**; *Embedded software.*

KEYWORDS

Connected and autonomous vehicles, intersection management, mixed-traffic.

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1 INTRODUCTION

Due to the advances of vehicle-to-everything communication, sensing and control capability, and artificial intelligence, connected and autonomous vehicles (CAVs) can realize many revolutionary applications. CAVs present great potentials to improve safety and traffic performance and thus draw the attention of recent research. Particularly, intersection management for CAVs, including modeling, protocol design, scheduling, and analysis, is one of the highly-researched areas, due to the fact that intersections are the main sources of collisions and jams in urban traffic [4]. Furthermore, the similarity between intersections and other traffic scenarios called dynamic intersections [2], such as merging points, unprotected turns, single-track lanes, and construction zones, provides great extensibility to intersection management.

Related Work. Zheng *et al.* proposed a CAV protocol for intersection management [19], which introduces delay-awareness and verification capability into vehicular networked intersections. Zhao *et al.* proposed a scheduling method in an unsignalized intersection that takes multiple objectives to its scheduling purpose [18]. However, the aforementioned studies and many other CAV-related studies [5, 10, 17] assume that the traffic consists of CAVs only, without any human-driving vehicle (HV), which is unlikely in the near future [6]. Considering the principle that HVs do not change their behaviors to accommodate the presence of CAVs [1], it is challenging to fully utilize CAVs' potentials. Aoki *et al.* [3] proposed a mixed-traffic intersection protocol where the system falls back to a signalized intersection whenever an HV is present. Similarly, CAVs in other mixed-traffic intersection protocols [7, 11] also suffer performance loss due to the presence of HVs since the systems have to reserve all possible trajectories of HVs or add more restrictions. Furthermore, if there exist non-connected vehicles in a mixed-traffic environment, scheduling is more difficult as only a portion of the traffic is cooperative. Therefore, some studies [14, 16] that aim to further improve safety or traffic performance in a mixed-traffic environment focus on optimizing the single-vehicle control of a CAV rather than cooperative scheduling which is more effective with pure CAV traffic.

Motivations. Inspired by the study that utilizes CAVs to stabilize traffic [13], we intend to schedule CAVs to control (block, in some sense) the subsequent HVs for mixed-traffic intersection management. Combining the observation in the previous studies of mixed-traffic intersection management where the presence of HVs hinders the performance of CAVs, we see an opportunity for the blocking strategy to mitigate the performance loss, if we can reduce the interference from HVs with CAVs. An example is illustrated in Figure 1(a). Without the blocking strategy, CAV A passes through the intersection first as it arrives at the intersection first (in a first-come-first-served manner), leaving CAVs B, C, and D to pass through the intersection with the presence of HV E, as shown in Figure 1(b), and resulting in performance loss (CAVs B, C, and D need to move slower). However, as shown in Figure 1(c), if we control CAV A to block HV E (which is behind CAV A), CAVs B, C, and D can pass through the intersection without the presence of HV E, and the overall performance (*e.g.*, the

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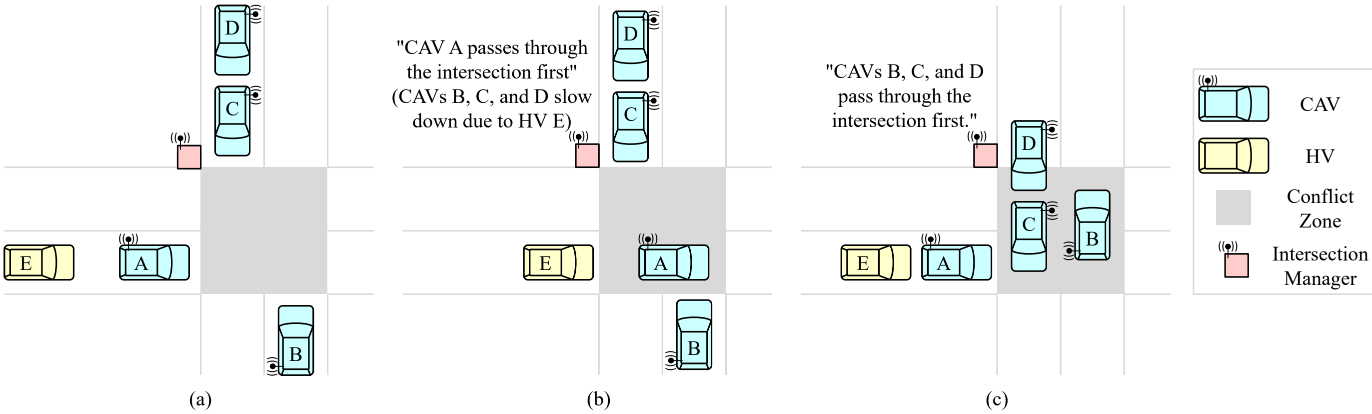


Figure 1: (a) An example of mixed-traffic intersection management. (b) Without the blocking strategy, CAV A passes through the intersection first as it arrives at the intersection first (first-come-first-served), leaving CAVs B, C, and D to pass through the intersection with the presence of HV E, and resulting in performance loss. (c) If we control CAV A to block HV E, CAVs B, C, and D can pass through the intersection first without the presence of HV E, and the overall performance can be improved.

average delay of all vehicles) can be improved (CAVs B, C, and D can move faster).

Contributions. In this paper, we target the problem of mixed-traffic intersection management consisting of CAVs and HVs. We consider a single conflict zone model and a general trajectory-based model for intersections. The main contributions include:

- We schedule CAVs to control the subsequent HVs. We develop a dynamic programming approach to the single conflict zone model and a MILP formulation for the trajectory-based model. Both of them solve the corresponding problems optimally.
- We propose an MILP-based approach which is more efficient and real-time-applicable than solving the optimal MILP formulation, while keeping good solution quality as well as outperforming the first-come-first-served (FCFS) approach.
- Experimental results and SUMO simulation [9] indicate that controlling CAVs by our approaches is effective to regulate mixed-traffic even if the CAV penetration rate is low, which brings incentive to early adoption of CAVs.

Organization. The rest of the paper is organized as follows. Section 2 introduces the system models and the problems. Section 3 presents our approaches to the problems. Section 4 demonstrates the experimental results. Section 5 concludes this paper.

2 SYSTEM MODELS AND PROBLEMS

In this section, we first introduce a single conflict zone intersection model and then present a general trajectory-based intersection model, where vehicles with non-conflicting trajectories can pass through the intersection at the same time to better match real-world scenarios.

2.1 Single Conflict Zone Model

As shown in Figure 1, the intersection is modeled as one conflict zone with overtaking-prohibited mixed-traffic including CAVs and HVs. The intersection behaves depending on whether there exists an HV at the head (as the first vehicle) on at least one lane. If yes, the CAVs have to use an HV-compatible protocol due to the uncertain behaviors of HVs; otherwise, CAVs use a more efficient CAV protocol. With a single conflict zone, only a single vehicle can pass through the intersection at the same time. An HV passes through the intersection once it is the earliest arrived vehicle among the vehicles which have not passed through the intersection. A CAV follows the instructions from the intersection manager (according to the HV-compatible protocol and the CAV protocol) and passes through the intersection. We assume that the intersection manager knows the numbers and types (CAV or HV) of vehicles on each lane as well as the estimated arrival time of each vehicle.

We define the i-th vehicle on lane l as $v_{l,i}$. The following parameters are given:

- N: the total number of vehicles.
- L: the number of lanes.
- N_l: the number of vehicles on lane l.
- $H_{l,i}$: 1 / 0 if $v_{l,i}$ is an HV / CAV.
- $A_{l,i}$: the estimated arrival time of $v_{l,i}$.
- G: the time gap for the next passing vehicle if there is no HV at the head on each lane (when using the CAV protocol).
- G^+: the time gap for the next passing vehicle if there exists an HV at the head on a lane (when using the HV-compatible protocol).

Due to the uncertain behaviors of HVs, G^+ is larger than G.

Given the given parameters above, the problem is to decide the entering time of each vehicle, which is the time that the vehicle enters the intersection:

- $t_{l,i}$: the entering time of $v_{l,i}$.

The objective is to minimize the entering time of the last passing vehicle (which represents the performance of the intersection processing all vehicles):

$$\min \left(\max_{1 \le l \le L, 1 \le i \le N_l} t_{l,i} \right). \tag{2.1}$$

The following constraints need to be satisfied. First, overtaking is not allowed:

$$\forall (l,i), (l',i'), \quad l = l' \wedge i > i' \implies t_{l,i} \ge t_{l',i'}. \tag{2.2}$$

Second, the entering time of a vehicle must be after the estimated arrival time of the vehicle:

$$\forall (l,i), \quad t_{l,i} \ge A_{l,i}. \tag{2.3}$$

Third, the gap of the entering times of two consecutive vehicles must be large enough to maintain a safe time gap which depends on whether there exists an HV at the head (as the first vehicle) on at least one lane:

$$\forall (l, i), (l', i'), \qquad \text{IsNext}(l, i, l', i') \implies t_{l,i} - t_{l',i'} \geq \text{TimeGap}(l, i), \tag{2.4}$$

where

$$\text{IsNext}(l, i, l', i') = \begin{cases} 1, & v_{l,i} \text{ is the next passing vehicle after } v_{l',i'}; \\ 0, & \text{otherwise,} \end{cases} \tag{2.5}$$

$$\text{TimeGap}(l, i) = \begin{cases} G^+, & \text{there exists an HV at the head on a lane when } v_{l,i} \text{ is passing;} \\ G, & \text{otherwise.} \end{cases} \tag{2.6}$$

Last, we can only schedule CAVs, not HVs, so if an HV arrives at the intersection first compared to another vehicle, it does not yield:

$$\forall (l, i), (l', i'), \quad A_{l,i} < A_{l',i'} \wedge H_{l,i} \implies \neg\text{IsAtHead}(l, i, l', i'), \tag{2.7}$$

where

$$\text{IsAtHead}(l, i, l', i') = \begin{cases} 1, & v_{l,i} \text{ is at the head on its lane when } v_{l',i'} \text{ is entering the intersection;} \\ 0, & \text{otherwise.} \end{cases} \tag{2.8}$$

2.2 Trajectory-Based Model

The single conflict zone model restricts that only a single vehicle can pass through the intersection at the same time. The trajectory-based model allows vehicles with non-conflicting trajectories to pass through the intersection at the same time to better match real-world scenarios. We denote the pairs of non-conflicting vehicles as a set:

- Γ: the set of (l, i, l', i') where $v_{l,i}$ and $v_{l',i'}$ have no trajectory conflict.

We then adjust the passing time in Equation (2.4) in the previous section to:

$$\forall l, l', i, i', \qquad \text{IsAfter}(l, i, l', i') \implies t_{l,i} - t_{l',i'} \geq \text{TimeGap}'(l, i, l', i'), \tag{2.9}$$

where

$$\text{IsAfter}(l, i, l', i') = \begin{cases} 1, & v_{l,i} \text{ passes not before } v_{l',i'}; \\ 0, & \text{otherwise,} \end{cases} \tag{2.10}$$

$$\text{TimeGap}'(l, i, l', i') = \begin{cases} \text{TimeGap}(l, i), & \text{if } (l, i, l', i') \notin \Gamma; \\ 0, & \text{if } (l, i, l', i') \in \Gamma. \end{cases} \tag{2.11}$$

Note that a strict passing order does not exist in the trajectory-based model, so we replace IsNext(l, i, l', i') in Equation (2.4) by IsAfter(l, i, l', i') to consider all vehicles (not only the next vehicle) after a passing vehicle.

3 APPROACHES

In the following sections, we present a dynamic programming approach to the single conflict zone model and solve the trajectory-based model by an MILP formulation as well as an efficient and real-time-applicable MILP-based approach.

3.1 Dynamic Programming

The dynamic programming approach in this section solves the single conflict zone model in Section 2.1 optimally. For lane l, we denote the number of vehicles which have passed through the intersection as θ_l. Given a state $\Theta = (\theta_1, \theta_2, \ldots, \theta_L)$, the previous state must be $\Theta' = (\theta'_1, \theta'_2, \ldots, \theta'_L)$ with exactly one l such that $\theta'_l = \theta_l - 1$ and each other l' such that $\theta'_{l'} = \theta_{l'}$. The transition from Θ' to Θ means that v_{l,θ_l} passes through the intersection, and the objective only depends on the time gap for v_{l,θ_l}. Therefore, the optimality holds with the subproblems.

If all vehicles are CAVs, we can use dynamic programming to solve the subproblem OBJ(Θ):

$$\min_l \left(\max \left(A_{l,\theta_l}, \text{OBJ}\left(\Theta'_l\right) + \text{TimeGap}\left(\Theta'_l, l\right) \right) \right), \tag{3.1}$$

where OBJ(Θ) is the maximum entering time of $v_{1,\theta_1}, v_{2,\theta_2}, \ldots, v_{L,\theta_L}$, and the time gap depends on the types of the passing vehicle and the vehicles at the heads on the other lanes:

$$\text{TimeGap}(\Theta, i) = \begin{cases} G^+, & H_{1,\theta_1+1} \vee H_{2,\theta_2+1} \vee \cdots \vee H_{i,\theta_i} \vee H_{i+1,\theta_{i+1}+1} \vee \cdots \vee H_{L,\theta_L+1}; \\ G, & \text{otherwise.} \end{cases} \tag{3.2}$$

Note that $H_{l,N_l+1} = 0$, meaning that all vehicles on lane l have passed through the intersection. OBJ$((N_1, N_2, \ldots, N_L))$ provides the optimal solution to the overall problem.

However, we can only schedule CAVs as Equation (2.7), and thus some state transitions are not allowed. Therefore, we need to adjust the subproblem OBJ(Θ):

$$\min_l \left(\max \left(A_{l,\theta_l}, \text{OBJ}\left(\Theta'_l\right) + \text{TimeGap}\left(\Theta'_l, l\right), \text{Legal}\left(\Theta'_l, l\right) \right) \right), \tag{3.3}$$

where

$$\text{Legal}(\Theta, i) = \begin{cases} \infty, & \exists j, j \neq i, H_{j,\theta_j+1} \wedge \left(A_{j,\theta_j+1} < A_{i,\theta_i+1} \right); \\ 0, & \text{otherwise.} \end{cases} \tag{3.4}$$

Similarly, OBJ$((N_1, N_2, \ldots, N_L))$ provides the optimal solution to the overall problem. The time complexity of this algorithm is $O(N_1 \cdot N_2 \cdot \cdots \cdot N_L)$.

3.2 MILP Formulation

The MILP formulation in this section solves the trajectory-based model in Section 2.2 optimally, where vehicles with non-conflicting trajectories can pass through the intersection at the same time. In the MILP formulation below, M represents a sufficient large constant.

3.2.1 Variables. The variables in the MILP formulation include:

- $t_{l,i}$: the entering time of $v_{l,i}$.
- $h_{l,i,l',i'}$: the binary variable indicating whether $v_{l',i'}$ is at the head on its lane when $v_{l,i}$ is passing through the intersection.
- $h_{l,i,l',N_{l'}+1}$: the binary variable indicating whether all vehicles on lane l' have passed through the intersection when $v_{l,i}$ is passing through the intersection.
- $o_{l,i,l',i'}$: the binary variable indicating whether $v_{l,i}$ passes before $v_{l',i'}$.
- $r_{l,i}$: the binary variable indicating whether there exists an HV (including $v_{l,i}$ itself) at the head on at least one lane when $v_{l,i}$ is passing through the intersection.
- $z_{l,i}$: the binary variable indicating whether $v_{l,i}$ is the last passing vehicle.

The variable $h_{l,i,l',i'}$ is set by:

$$\forall(l,i), \qquad h_{l,i,l,i} = 1; \tag{3.5}$$

$$\forall(l,i), l' \neq l, \qquad \sum_{i',1\leq i'\leq N_{l'}+1} h_{l,i,l',i'} = 1; \tag{3.6}$$

$$\forall(l,i), l' \neq l, \qquad \sum_{i',1\leq i'\leq N_{l'}} o_{l',i',l,i} + 1 = \sum_{i',1\leq i'\leq N_{l'}+1} i' h_{l,i,l',i'}. \tag{3.7}$$

The variable $o_{l,i,l',i'}$ is set by, for all different $(l,i),(l',i'),(l'',i'')$:

$$o_{l,i,l',i'} + o_{l',i',l,i} = 1, \quad o_{l,i,l',i'} + o_{l',i',l'',i''} - 1 \leq o_{l,i,l'',i''}. \tag{3.8}$$

The variable $r_{l,i}$ is set by:

$$\forall(l,i), \quad \sum_{l',i'} H_{l',i'} h_{l,i,l',i'} \leq M r_{l,i}. \tag{3.9}$$

The variable $z_{l,i}$ is set by:

$$\sum_{l,i} z_{l,i} = 1; \quad \forall(l,i), \quad \sum_{l',i'} h_{l,i,l',i'} + M\left(z_{l,i} - 1\right) \leq 0. \tag{3.10}$$

3.2.2 Objective. The objective of the MILP formulation is:

$$\min \quad \max_{l}\left(t_{l,N_l}\right). \tag{3.11}$$

Note that it can be transformed to $\min Z$, where $t_{l,N_l} \leq Z$ for all l.

3.2.3 Constraints. The four constraints in Section 2 are transformed to the following constraints in the MILP formulation. Equation (2.2) is transformed to:

$$\forall(l,i),(l,i'), i < i', \quad o_{l,i,l,i'} = 1, \quad o_{l,i,l,i} = 0. \tag{3.12}$$

This means that overtaking is not allowed. Equation (2.3) is transformed to:

$$\forall(l,i), \quad t_{l,i} \geq A_{l,i}. \tag{3.13}$$

This means that the entering time of a vehicle must be after the estimated arrival time of the vehicle. Equation (2.9) which updates Equation (2.4) for the trajectory-based model is transformed to two cases. When there is no HV at the head on each lane:

$$\forall(l,i,l',i') \notin \Gamma, \quad t_{l',i'} - t_{l,i} + M\left(1 - o_{l,i,l',i'}\right) + M z_{l,i} \geq G; \tag{3.14}$$

$$\forall(l,i,l',i') \in \Gamma, \quad t_{l',i'} - t_{l,i} + M\left(1 - o_{l,i,l',i'}\right) + M z_{l,i} \geq 0. \tag{3.15}$$

When there exists an HV at the head on at least one lane:

$$\forall(l,i,l',i') \notin \Gamma, \tag{3.16}$$
$$t_{l',i'} - t_{l,i} + M\left(1 - o_{l,i,l',i'}\right) + M z_{l,i} \geq G^{+} + M(r_{l,i} - 1).$$

The two cases mean that the gap of the entering times of two consecutive vehicles must be large enough to maintain a safe time gap which depends on whether there exists an HV at the head on at least one lane. Equation (2.7) is transformed to:

$$\forall(l,i),(l',i'), l \neq l', \quad M\left(h_{l,i,l',i'} H_{l',i'}\right) + \left(A_{l,i} - A_{l',i'}\right) \leq M. \tag{3.17}$$

This means that an HV does not yield another vehicle if it arrives at the intersection first.

3.3 MILP-Based Approach

The MILP-based approach in this section solves the trajectory-based model in Section 2.2 in a more efficient and real-time applicable way, but it cannot guarantee the optimality. The fundamental concept of the MILP-based approach is to split the MILP formulation into smaller subproblems, solve them, and merge the results.

We generalize the MILP formulation in Section 3.2 as MILP(V,T), where V is a subset of all vehicles and T is a timing constraint such that:

$$\forall(l,i), \quad t_{l,i} \geq T. \tag{3.18}$$

It is clear that the MILP formulation in Section 3.2 is a special case where V is the set of all vehicles and $T = 0$.

The MILP-based approach works as follows. Given MILP(V,T), if $|V|$ is small enough, we solve MILP(V,T) as the MILP formulation in Section 3.2 with the timing constraint (Equation (3.18)). Otherwise, if $|V|$ is large, we set V' as a subset of V, where V' consists of $|V'|$ vehicles with the least estimated arrival times in V (to satisfy Equations (3.12) and (3.17).) Then, we solve MILP(V',T) and MILP$(V \setminus V', T')$ where T' is the objective of MILP(V',T) plus G^{+}. The MILP-based approach cannot guarantee the optimality, but it provides a linear time complexity to $|V|$ as long as $|V'|$ is a positive constant.

4 EXPERIMENTAL RESULTS

In this section, we demonstrate the experimental results. The experiments were run on a laptop with 1.8GHz Intel Core i7-8550U processor and 16GB memory. We use Gurobi as the MILP solver. Due to uncontrollable HVs in mixed-traffic, existing studies on mixed-traffic focus on protocol design (*e.g.*, switching to signalized intersection management with the presence of HVs) or single-vehicle control rather than system-wide scheduling. Therefore, we will compare our approaches with the FCFS approach. The FCFS approach is optimal for the single conflict zone model when all vehicles are of the same type.

4.1 Single Conflict Zone Model

We consider 4 lanes as shown in Figure 1, 10 vehicles on each lane, $G = 1$ (second), $G^{+} = 3$ (second), and a Poisson arrival with $\lambda = 0.5$ vehicle per second. We compare our dynamic programming approach with the FCFS approach which schedules vehicles according to their estimated arrival times.

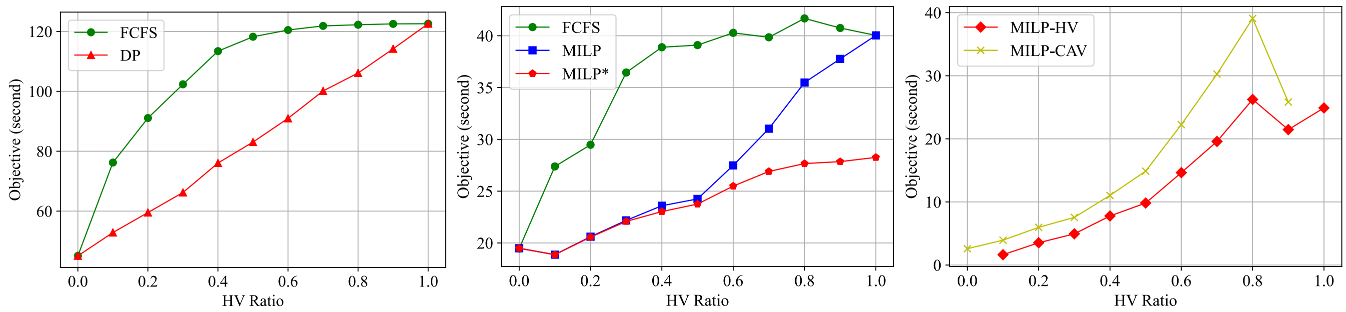
Figure 2(a) shows the experimental results. The dynamic programming approach returns an optimal approach and has a better objective when the HV ratio is between 0.1 and 0.9 because it tends to group CAVs together and prevents them from being interrupted by HVs which require a larger time gap. When the HV ratio is 0 or 1, where all vehicles' time gaps are G or all vehicles are not controllable, both approaches are optimal. The average runtime of the dynamic programming approach is 0.51 second.

We further observe that the objective of the dynamic programming approach with respect to the HV ratio is rather linear, compared with the FCFS approach. This brings the insight that even early adoption of CAVs, scheduled by the dynamic programming approach (not by the FCFS approach which starts to gain clear benefit when the CAV penetration rate is up to 0.5), can significantly improve the traffic performance.

4.2 Trajectory-Based Model

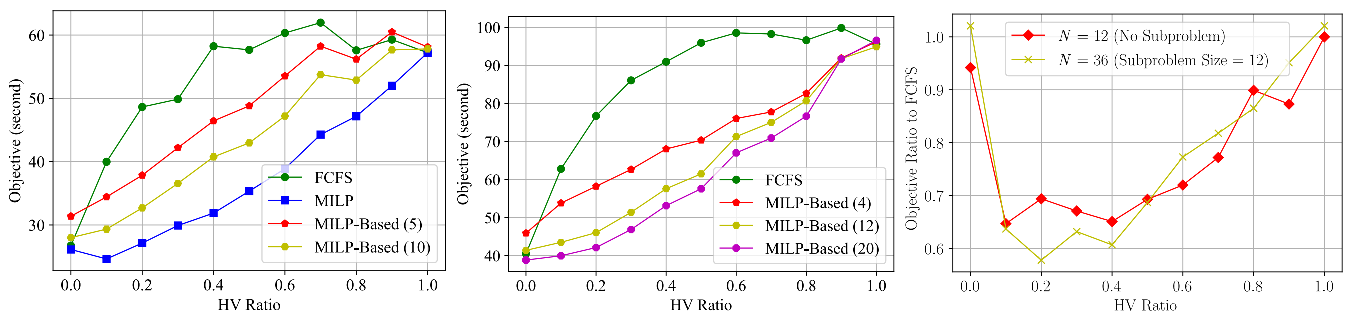
4.2.1 MILP Formulation. We consider 4 lanes, 5 vehicles on each lane, $G = 1$ (second), $G^{+} = 3$ (second), and a Poisson arrival with $\lambda = 0.5$ vehicle per second. We compare our MILP formulation with the FCFS approach. We are also interested in how effective CAVs are to support mixed-traffic intersection management, so we also perform experiments assuming that HVs are controllable as CAVs.

Figure 2(b) shows the experimental results. The MILP formulation returns an optimal solution and has a better objective than the FCFS approach when the HV ratio is between 0.1 and 0.9. Similar to the dynamic programming approach in the previous section, the objective of the MILP formulation with respect to the HV ratio is also



(a) (b) (c)

Figure 2: (a) Comparison between the FCFS approach and the dynamic programming (DP) approach for the single conflict zone model. (b) Comparison between the FCFS approach and the MILP formulation (including experiments assuming that HVs are controllable as CAVs, marked as MILP*) for the trajectory-based model. (c) The average waiting times of CAVs and HVs in the MILP formulation. The objective is the entering time of the last vehicle.



(a) (b) (c)

Figure 3: (a) Comparison between the FCFS approach, the MILP formulation, and the MILP-based approach with small test cases for the trajectory-based model. (b) Comparison between the FCFS approach and the MILP-based approach with large test cases for the trajectory-based model. (c) The objective ratio of the MILP-based approach to the FCFS approach. The objective is the entering time of the last vehicle. A number in the parentheses is the subproblem size of the MILP-based approach.

rather linear, supporting early adoption of CAVs again. Furthermore, if HVs are controllable, the objective is reduced significantly only when the HV ratio is above 0.5, bringing the insight that controlling half vehicles, with our blocking strategy, is almost as effective as controlling all vehicles.

Figure 2(c) shows the average waiting times ($t_{l,i} - A_{l,i}$ for $\mu_{l,i}$) of CAVs and HVs in the MILP formulation. We can observe that the waiting time of CAVs is larger than that of HVs. This is because, when the waiting time of an HV increases, it means that the HV is blocked by a CAV and implies that the waiting time of the CAV also increases. This indicates that our MILP formulation controls CAVs which suffer extra waiting times but improves the overall traffic performance.

The average runtime of solving the MILP formulation is 0.42 second. It should be noted that we have also modified the dynamic programming approach by introducing a time state as Wu *et al.* [15] to fit in the trajectory-based model. The modified approach also returns an optimal solution as the MILP formulation but takes about 1 minute. Due to the much longer runtime and the limitation of space, we do not consider the modified approach in the following experimental results.

4.2.2 MILP-Based Approach (Small Test Cases). We consider 4 lanes and 5 vehicles on each lane with the same parameters as above. We compare our MILP-based approach with the FCFS approach and the MILP formulation. Figure 3(a) shows the experimental results. When the subproblem size increases, the objective decreases (is better) for the MILP-based approach, which is expected. It should be noted that when the subproblem size is the number of vehicles, the MILP-based approach is equivalent to the MILP formulation which returns an optimal solution. The MILP-based approach significantly outperforms the FCFS approach in almost all cases, especially when the HV ratio is not 0 or 1. The average runtimes of the MILP-based approach with subproblem sizes 5 and 10 are 0.01 and 0.05 second, respectively, which are much more efficient than solving the MILP formulation with 0.48 second.

4.2.3 MILP-Based Approach (Large Test Cases). The average runtime of solving the MILP formulation grows exponentially as the number of vehicles increases. When the number of vehicles reaches 32, the average runtime is about 1 minute, making the MILP formulation inapplicable in large test cases. Here, We consider 4 lanes and 10 vehicles on each lane with the same other parameters as above. We compare our MILP-based approach with the FCFS approach. Figure 3(b) shows the experimental results. Similarly, when the subproblem size increases, the objective decreases (is better) for the MILP-based approach. The MILP-based approach also significantly outperforms the FCFS approach in all cases, except when the HV ratio is 0 or 1. Figure 3(c) shows the objective ratio of the MILP-based approach

Table 1: SUMO Simulation Parameters.

Type	Parameter	Value
Simulation	Simulation Step	0.1 (s)
	Road Length	500 (m)
Intersection Manager	Sensing Range	100 (m)
	Scheduling Period	1 (s)
Vehicle	Max Speed	16 (m/s)
	Max Acceleration/Deceleration	3/-4.5 (m/s^2)
	Min Gap	2.5 (m)
	Vehicle-Following Model	Krauss Model [12]

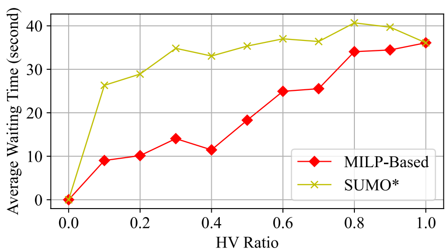


Figure 4: Simulation results on SUMO. SUMO* is the SUMO unsignalized intersection [8] with modifications using TraCI to fit our assumption that CAVs move slower with the presence of HVs.

to the FCFS approach when the numbers of vehicles are 12 and 36. When the HV ratio is low, the improvement over the FCFS approach is more significant, which is also consistent with the results above. The average runtimes of the MILP-based approach with subproblem sizes 4, 12, and 20 are 0.01, 0.08, and 0.42 second, respectively, which are real-time applicable.

4.2.4 SUMO Simulation. We perform simulation on SUMO [9] and consider 4 lanes as shown in Figure 1. The parameters are listed in Table 1, and $\lambda = 0.1$ vehicle per second is set for the Poisson arrival of vehicles (the arrival rate needs to be lower than the previous experiments due to additional safety constraints and vehicle dynamics on SUMO). As the traffic is coming continuously in the simulation, we measure the average waiting time of vehicles. We implement the MILP-based approach and control vehicles according to the computed entering times by the traffic control interface (TraCI) on SUMO. We compare it with the SUMO unsignalized intersection [8] with modifications using TraCI to fit our assumption that CAVs move slower with the presence of HVs. Figure 4 shows the simulation results, and the MILP-based approach significantly outperforms the counterpart. We believe that the results can be further improved if the model can consider the additional safety constraints and vehicle dynamics of SUMO, but it will also trade off the computational efficiency.

5 CONCLUSION

In this paper, we targeted the problem of mixed-traffic intersection management and scheduled CAVs to control the subsequent HVs. We developed a dynamic programming approach and a mixed integer linear programming (MILP) formulation to optimally solve the problems with the corresponding intersection models. We then proposed an MILP-based approach which is more efficient and real-time-applicable than solving the optimal MILP formulation, while keeping good solution quality as well as outperforming the first-come-first-served (FCFS) approach. Experimental results and SUMO simulation indicated that controlling CAVs by our approaches is effective to regulate mixed-traffic even if the CAV penetration rate is low, which brings incentive to early adoption of CAVs. Future directions include management with specific lanes for CAVs and HVs and management considering different dynamics of CAVs and HVs.

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