Intersection control with connected and automated vehicles: a review

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Abstract

Purpose – This paper aims to review the studies on intersection control with connected and automated vehicles (CAVs).

Design/methodology/approach – The most seminal and recent research in this area is reviewed. This study specifically focuses on two categories: CAV trajectory planning and joint intersection and CAV control.

Findings – It is found that there is a lack of widely recognized benchmarks in this area, which hinders the validation and demonstration of new studies.

Originality/value – In this review, the authors focus on the methodological approaches taken to empower intersection control with CAVs. The authors hope the present review could shed light on the state-of-the-art methods, research gaps and future research directions.

Keywords Connected and automated vehicles, Intersection control, Trajectory planning, Optimization

Paper type Literature review

1. Introduction

Road intersections are where conflicting traffic flows are forced to share the limited spatiotemporal resources and thus often cause the most delay, emission and accidents in urban transport systems. Ever since the first documented implementation of traffic lights in London in 1868, the management of intersections has been at the heart of transport engineering. Generations of transport academics and engineers devoted enormous efforts to advancing the knowledge of intersection control and optimization (Dion *et al.*, 2004; Qu and Wang, 2021; Wadud and Mattioli, 2021; Wu *et al.*, 2019; Xu *et al.*, 2022). However, although one and a half centuries have passed, we still heavily rely on traffic lights in controlling traffic flows at intersections, because the signals are unfortunately the only component that can be controlled. The emerging connected and automated vehicle (CAV) technology shows a promising future of urban transportation, where travelers, vehicles and infrastructures can be reached and controlled for the first time (Lee and Hess, 2020; Larsson *et al.*, 2021; Ortúzar, 2021; Rad *et al.*, 2021; Tan *et al.*, 2022; Wang *et al.*, 2022a, 2022b). Vehicle-to-vehicle (V2V) communication, vehicle-to-infrastructure (V2I) communication and autonomous driving technologies are widely regarded as the key enablers for the development of next-generation intelligent transport systems and are highly anticipated to bring new solutions to the most concerned transportation problems. On top of the list is the management of road intersections.

In this fast-growing area, it has been more than three years since the last related review was conducted by Guo, *et al.* (2019), during which an abundance of new concepts, methods and field experiments were proposed and conducted. This calls for a re-examination of the state-of-the-art knowledge to identify the prevailing research orientations, most advanced models and algorithms, widely used benchmarks and research gaps. To this end, we present such a review in the present paper. Except for a regular update of references, this review differentiates itself from previous ones with a focus on the management of isolated intersections, whereas previous reviews often cover a wide range of infrastructures on different scales, such as ramps, corridors and signal networks (Rios-Torres and Malikopoulos, 2017). Specifically, we seek to deepen the understanding of isolated intersection management because it is the foundation for research on larger scales, and it has not been satisfactorily resolved yet. Along this line, we target two mainstreams of research in this area, i.e. CAV trajectory planning at signalized intersections and joint CAVs

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control and traffic signal optimization. For each stream, we will focus on the key setups, strengths and limitations of the most widely used methodological paradigms. We hope the present work could help new readers fast familiarize the frontiers and motivate experienced researchers to tackle the most challenging problems in this area.

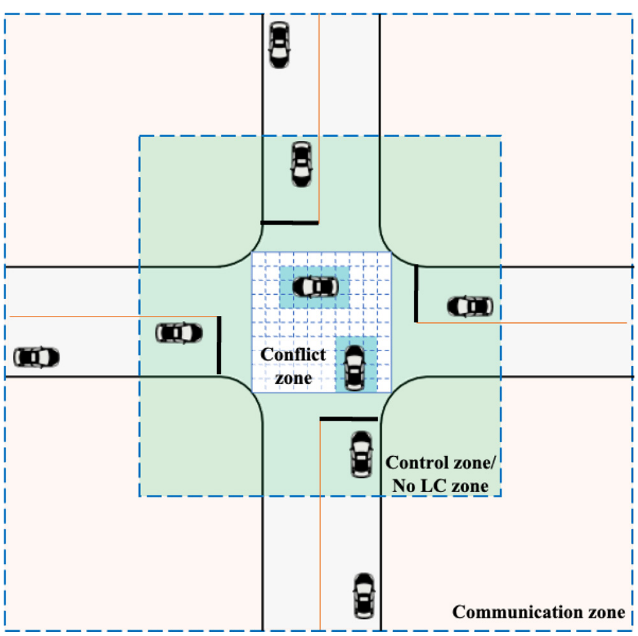
For the convenience of communication, Figure 1 is used throughout the paper in which an intersection is divided into three nested zones, i.e. the conflict zone, control zone and communication zone. Different papers may have diverse numbers of sizes of zones, depending on the applied methods and setups, but Figure 1 should facilitate the introduction of most studies based on our experience. In most cases, the conflict zone is only highlighted in autonomous intersection management (AIM) studies where all the vehicles are CAVs and thus traffic signals can be potentially removed; the control zone often defines the area where CAVs must follow the designed trajectories or cannot make lane changings; the communication zone is practically defined by the communication range where solution calculations or lane changings are conducted. We would also like to clarify that steering control is beyond the scope of this review, and we always assume that CAVs can perfectly follow the designed trajectories.

The remainder of the paper will be arranged as follows. Section 2 reviews the advances in CAV trajectory design at intersections. Section 3 presents the state-of-the-art methods for the joint control of CAVs and intersections. Section 4 concludes the paper with discussions.

2. Connected and automated vehicle trajectory planning

Advanced driver-assistance systems are nowadays common add-ons for commercialized vehicles, which could to some extent relieve drivers from disturbing tasks, such as lane keeping and maintaining a constant speed (Zhou *et al.*, 2020). With CAVs, it is reasonable to expect that vehicles could perform more

Figure 1 Different zones for CAV and intersection control



demanding and sophisticated tasks by following well-designed trajectories. At signalized intersections, the trajectories can be designed to catch a green light, reduce emission, alleviate oscillations and the list goes on. This idea is explored by a large body of research, as it is the most fundamental application of CAV innovation. In this section, we review the key methods used in CAV trajectory planning at signalized intersections, as well as the findings and research gaps.

In this direction, the traffic signal control plan is usually an input instead of a set of decision variables, so fixed-time control is often used to generate a stationary and reproducible context. Based on whether lane changings are involved, studies can be generally divided into two categories, i.e. single-lane trajectory planning and multi-lane trajectory planning.

2.1 Single-lane trajectory planning

Given that the signal timing is fixed, and lane changings are omitted, the CAV trajectory design problem is inherently equivalent to the CAV car-following control problem in a signalized intersection context. Regardless of the objective function and the methods used, one can usually see smooth trajectories passing intersections without stops, as illustrated in Figure 2. We hereby introduce recent advances in CAV trajectory planning at single-lane intersections from model-based and learning-based perspectives. Note that we also consider studies that have a multi-lane setup but forbid lane changings as single-lane intersection research, as only longitudinal trajectory planning is concerned, for example, in the paper from Chen *et al.* (2021).

2.1.1 Model-based connected and automated vehicle trajectory planning

In the car-following control of CAVs, control theory serves as the backbone of the analytical framework because the system status can be well described by a set of state and input vectors. Without losing generality, the control problem can be formulated as follows.

$$\min_{\mathbf{u}} \mathcal{J}(\mathbf{x}, \mathbf{u})$$

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t)) \tag{2}$$

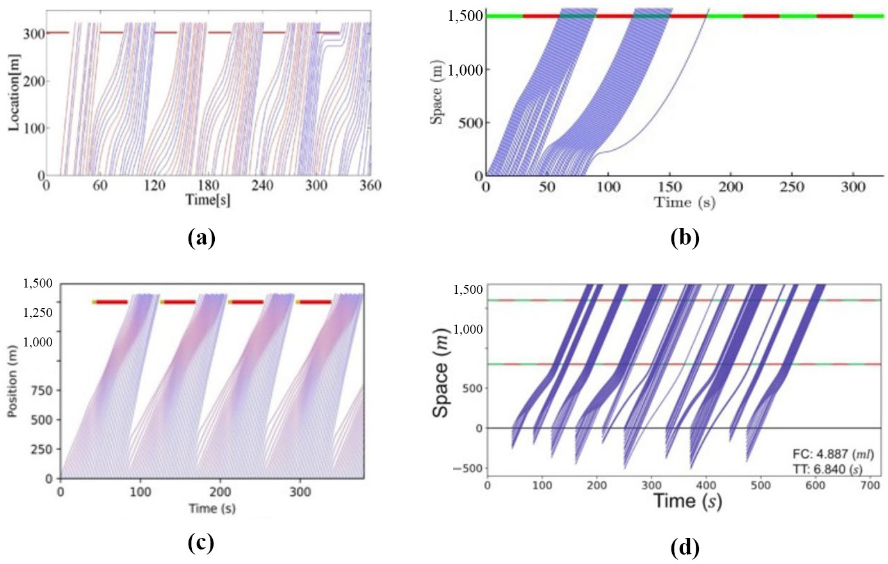
$$\mathbf{u}(t) \in \mathcal{U} \tag{3}$$

$$\mathbf{x}(0) = \mathbf{x}_0 \tag{4}$$

where $\mathcal{J}(\mathbf{x},\mathbf{u})$ is a general objective function that can be formulated based on the optimization purposes; $\dot{\mathbf{x}}$ denotes the system state vector and is usually characterized by vehicle position and speed; $\mathbf{u}(t)$ is the constrained control input, for which most existing studies use the vehicle acceleration rate as a convenient differential extension for the system state vectors; $\mathbf{x}(0)$ denotes the initial condition. With the above formulation, the abundance of control theories can be directly applied to solve the optimal trajectory planning problem, such as the model predictive control methods.

In this approach, Wang *et al.* (2014a) proposed a rolling horizon control framework for the car-following problem of CAVs. In their work, it is demonstrated how the objective function in equation (1) can be tailored to fulfill different control objectives such as safety penalties and realize diverse control

Figure 2 Examples for CAV trajectory planning results at isolated intersections



Notes: (a) Jiang *et al*. (2017); (b) Ma *et al*. (2017); (c) Zhou *et al*. (2020); (d) Han *et al*. (2020)

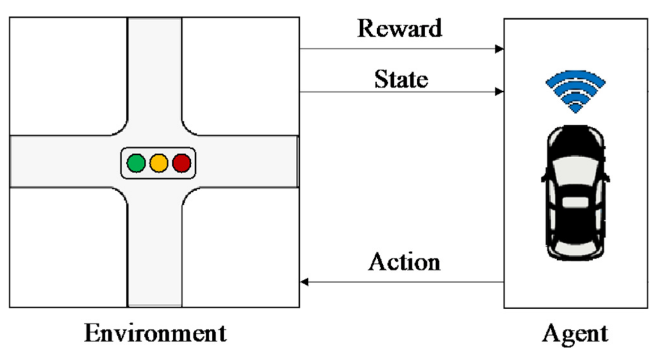
strategies, for example, the constant time gap policy. In a following study, they extend the methodology to the modeling of cooperative CAV and human-driven vehicle (HDV) platoons (Wang *et al.*, 2014b). Zhou *et al.* (2017) further developed a stochastic optimal control model following the same rolling horizon control framework by considering the uncertainties in the measurement of system states. Other key problems, e.g. communication constraints, platoon string stability and computational performances, were also examined under the control theory framework (Montanino and Punzo, 2021; Talebpour and Mahmassani, 2016; Wang *et al.*, 2019; Zhou *et al.*, 2019; Zhou *et al.*, 2020).

The control theory-based CAV trajectory planning enjoys several strengths in problem-solving. First, the objective function can be easily tailored to fulfill different optimization goals. Second, explicit formulations enable a clear understanding of the problem and reproducible results. Last but not least, closed-form solutions can sometimes be achieved, which is highly favorable in field implementations. With profound models, car-following control can easily extend to CAV trajectory planning at single-lane intersections. The most notable application is eco-driving. Jiang *et al.* (2017) proposed an eco-driving framework for an isolated intersection with mixed CAV and HDV platoons. Significant fuel consumption reductions (2.02% to 58.01%) and improvements on throughput volume were observed due to the proposed control methods. Chen *et al.* (2021) developed a platoon-based control framework for the optimization of traffic efficiency and fuel consumption. In the control zone as illustrated in Figure 1, CAVs will lead and regulate a platoon of human drivers, and the control framework in equations (1)–(4) was applied to design trajectories. Zhang *et al.* (2021) proposed a wireless charging scheme for connected automated, and electric vehicles. The key idea is to deploy a partial wireless charging lane to utilize the slow movement of CAVs at the intersection. However, under scenarios when closed-form solutions cannot be found, those sophisticated models can still suffer from overly long computational time which inspired heuristic-based trajectory planning models, such as the parsimonious shooting algorithm (Ma *et al.*, 2017; Zhou *et al.*, 2017).

2.1.2 Learning-based connected and automated vehicle trajectory planning

Except for the aforementioned model-based approach, recent studies start to explore the possibility of designing CAV trajectories with state-of-the-art machine learning technologies, especially reinforcement learning (RL) models (Peng *et al.*, 2021). A general RL model consists of clearly defined agents, system states, a set of actions, transition functions and reward functions in a Markov decision process (MDP) (Sutton and Barto, 2005). Due to the MDP nature of vehicle control problems, RL has thus been increasingly implemented in the trajectory design of CAVs at isolated intersections. The methodological framework is illustrated in Figure 3. At each time step t, the ego vehicle receives an observation of the intersection s_t

Figure 3 RL framework for CAV trajectory planning at an isolated intersection



and a reward r_t from the environment. The behavior of the CAV is determined by a policy π, based on which the CAV generates a probability distribution of actions $P(a) = \pi(s_t)$.

In this area, Zhou *et al.* (2020) developed a RL-based car-following model for CAVs in a single-lane intersection scenario to improve the overall traffic efficiency, fuel consumption and traffic safety. Based on a comparative study with HDVs, the trained CAV controller significantly outperformed its counterpart and exhibited smooth trajectories instead of oscillations induced by the stop-and-go behaviors of human drivers. Chen *et al.* (2018) implemented a hierarchical RL algorithm for traffic light approaches, which first decides whether the controlled vehicle should stop or pass at a traffic light and then performs the corresponding longitudinal control accordingly. Shi *et al.* (2018) used traditional (non-deep) Q-learning to develop an efficient driving strategy for approaching signalized intersections. Mousa *et al.* (2020) used deep Q-learning with prioritized experience replay, target networks and double-learning to train an RL agent to approach and depart efficiently at signalized intersections for situations where no other vehicles are interfering. Wang *et al.* (2022a, 2022b) focused on the CAV control problem in mixed traffic flow at signalized intersections with particular considerations of the oscillations induced by human drivers. A deep RL model was developed to predict the trajectories of HDVs and control CAVs. Numerical experiments showed that the developed method could considerably improve the system performance even under a low penetration rate of CAVs (e.g. 10%). Other transportation applications of RL and deep reinforcement learning can be found in the comprehensive review presented by Haydari and Yılmaz (2022).

2.2 Multi-lane trajectory planning

In multi-lane scenarios, lane-changing (LC) is inevitable and thus has drawn increasing attention, as LC is a major source of traffic flow disturbance (Ali *et al.*, 2021). With CAVs, smooth and safe LC trajectories can be designed and precisely followed by smart vehicles (Larsson *et al.*, 2021). Further, using CAVs and control actuators, HDV LC behaviors could be to some extent regulated (Peng *et al.*, 2021). In the context of signalized intersections, both discretionary and mandatory LC exist, but discretionary LC gradually becomes the dominant one, as vehicles need to be in the desired lane group (left-turning, through-going and right-turning lanes) before reaching the stop line. Thus, the completion time is often involved as an additional objective or constraint. Completion time mainly consists of two parts, namely, the computation time for trajectory planning and the execution time, and consequently merits two research directions. Based on our review of existing studies, it is notable that the most efficient and best-performing algorithms have to cover both aspects, and thus it is intractable to completely separate the two research directions. However, to present a more structural review, we here cluster studies based on their primary focus.

Given computation time as a prioritized objective, decentralized methods are often favored in the trajectory planning of CAVs at intersections due to advantages in computational efficiency (Malikopoulos *et al.*, 2018; Yao and Li, 2020). For example, Ma *et al.* (2021) developed a decentralized trajectory planning method for both CAVs and connected HDVs. In their research, a bi-level optimization method was formulated to isolate the twisted LC and car-following problems. The upper level addressed the LC strategies, whereas the lower level optimized the longitudinal acceleration profile to solve the car-following control problem. To realize real-time implementation, several techniques were combined and applied, such as sequential processing, tree-searching and rolling horizon optimization. However, in such decentralized frameworks, it is theoretically possible that human drivers might cut in when a deliberately created gap emerges and compromise the expected trajectory planning results. To address this issue, Yao and Li (2021) developed a decentralized framework that adopts the LC aware concept for restraining discretionary lane changes but yielding mandatory lane changes. To expedite the solving of the formulated non-linear optimization problem, linearization was performed to enable the direct use of commercial solvers such as CPLEX and Gurobi. Compared to the baseline scenario where a LC awareness strategy is not included, the proposed method could yield a significant improvement in riding comfort, travel time, energy consumption and safety. For the same reason, machine learning-based models are extensively used in the control of CAVs in various scenarios for the well-known strength of solving complex problems in a reasonable time (Agostinelli *et al.*, 2019). Due to the nature of being a control problem, RL becomes the most prevailing framework in this area. For instance, Bai *et al.* (2022) developed a hybrid RL-based eco-driving strategy for mixed CAV and HDV traffic flows at signalized intersections. The strategy was demonstrated in a multi-lane intersection scenario through a unity-based simulator. Nevertheless, studies in this area are relatively rare probably due to the following three reasons:

1 the complexity brought by multi-lane LC coordination;
2 the uncertainties brought by human drivers; and
3 the constrained improvement when intersection control and optimization are excluded in the coordination.

Another major stream of research is to minimize the execution time by optimally designing CAV trajectories. Due to the high requirement of cooperation, studies in this approach often assume 100% CAV penetration rates. As intersection control is still excluded, the main motivation here is to develop general platoon control models and algorithms that can be applied to common road bottlenecks such as signalized intersections, highway ramps and work zones. The methodological frameworks in this area mainly stem from those widely used in multi-robot motion planning (González *et al.*, 2016; Paden *et al.*, 2016). For example, Wu *et al.* (2021) proposed a cooperative sorting algorithm for multi-lane CAV platoons, which can realize an optimal transition from any initial platoon permutation to any desired permutation. The algorithm relies on a discretization of the road section into a grid system with homogenous cells. Each CAV can occupy only one cell, and each cell can only accommodate one CAV. The sorting problem of the multi-lane platoon is further modeled as a shortest path finding problem in a hyper network in which each node represents a unique platoon permutation. A modified A* algorithm was developed to accelerate the searching with guaranteed optimality and compatibility with distributed computing techniques. Such techniques were commonly used in combinatorial optimization problems and games, such as the

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N-puzzle problem and Rubik's cube problem (Agostinelli *et al.*, 2019). However, in the problem of CAV platoon control, extra vehicle dynamic constraints and traffic-oriented objectives must be considered and integrated into the framework. The generality of the sorting algorithm was further demonstrated in their continuous research in different bottleneck scenarios, such as emergency vehicle preemption (Wu *et al.*, 2020) and work zone (Cao *et al.*, 2021). A similar framework was also used in the study of Cai *et al.* (2022), in which the A* algorithm was replaced with a conflict-based searching algorithm. The conflict-based searching algorithm is arguably faster than the A* algorithm because it is inherently a decentralized method and addresses trajectory conflicts "on the fly," whereas A* avoids conflicts in a centralized approach. In short, A* guarantees optimality but suffers from computation complexity; conflict-based searching enables fast computation but only generates sub-optimal solutions.

At signalized intersections, the above models could, as an example, realize flexible lane management and thus improve system efficiency. Specifically, as shown in Figure 4, if we could reorganize the CAV platoon and horizontally separate left-turning vehicles and through vehicles, all lanes can be used in both left-turning and through signal phases and consequently increase intersection capacity without changing the intersection control plan.

3. Joint intersection and connected and automated vehicle control

In this section, we review the most recent studies of joint control and optimization of intersections and CAVs. Research in this area represents the most complicated technology integration and seeks to fully exploit the potential of CAVs in improving the performance of intersections. Depending on whether physical traffic signals are used, we divide existing studies into two main categories: joint control at signalized intersections; and autonomous intersection management.

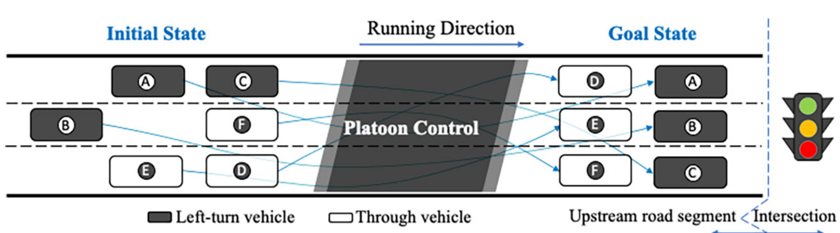
3.1 Joint control at signalized intersections

In the near future, jointly optimizing vehicle trajectories and signal control plans are probably the most anticipated and practical usage of CAV technology at intersections, but the problem is difficult. The convectional intersection signal control problem itself is in nature a combinatorial optimization problem, calling for the coordination of multiple dynamic traffic flows in both time and space. Vehicle trajectory planning can be also characterized by a combinatorial optimization approach in that vehicles interact with each other, all trying to pass the intersection safely and efficiently. The desire to simultaneously resolve both problems multiply the difficulty.

The most widely used method in this area is to model the joint control problem as a mathematical programming problem, such as mixed-integer linear programming (MILP), dynamic programming (DP) and nonlinear programming problems, which enables the direct usage of commercial solvers and state-of-the-art optimization techniques (Xu *et al.*, 2019; Yu *et al.*, 2018). The foundation of this modeling approach is that common decision variables in this type of problem are either integer (e.g. signal sequence, intersection leg index, vehicle index) or continuous variables (e.g. location, speed and acceleration rate), and thus the objectives and constraints can often be continently linearized (Chowdhury *et al.*, 2021; Hadjigeorgiou and Timotheou, 2022).

To simplify the optimization problem, a large number of studies decompose and reformulate the joint control problem into a bi-level or two-stage problem, each level or stage addressing one of the two twisted problems (i.e. signal optimization and CAV trajectory optimization). For example, Xu *et al.* (2018) proposed a two-step strategy for the joint optimal control problem. The first step optimized traffic signals and vehicles' arriving time with the objective to minimize the total delay of all vehicles. Based on the results from step one, the second step further optimizes vehicle trajectories to minimize fuel consumption. Their study assumed that when the vehicles enter the communication zone (Figure 1), all vehicles are already on the desired lanes so that the disturbances from lane changings are eliminated. VISSIM-based simulation experiments were conducted to demonstrate the performance of the proposed method. Results of the case studies reported a significant reduction in delay and emission. Similarly, Guo *et al.* (2019) also adopted a two-step approach to optimize traffic signals plan and CAV trajectories, respectively. For intersection control optimization, they developed a DP and shooting heuristic algorithm, which outperformed conventional adaptive control with a reduction of average travel time by up to 35.72% and energy consumption by up to 31.5%. For trajectory optimization, a numerical gradient-based approach was applied for best system performance realization. Such sequential decomposition of the joint control problem surely eases the solving of the complex optimization problem but inevitably loses optimality to a large extent. To this end, a few attempts have been made to directly solve the unified problem. Yu *et al.* (2018) proposed such a method by modeling the joint control problem as a MILP problem, in which signal phase sequences, green time start time and duration for each phase, cycle lengths and CAV trajectories were considered as control variables (that are to be optimized).

Figure 4 Platoon control at signalized intersections



For simplification, they created a no-LC zone inside of the control zone to reduce the solution space at the sacrifice of optimality. Liu *et al.* (2022) also developed a single-layer approach for the joint optimization problems through the MILP modeling approach. In their model, simplification is introduced by using fixed signal sequences and the forbidden of lane changings in the communication zone (Figure 1). Soleimaniamiri *et al.* (2020) developed an analytical optimization approach with a focus on real-time implementation. To reduce the computational burden, the vehicle trajectories were simplified as piece-wise quadratic functions, and macroscopic fuel consumption estimations are performed instead of using non-linear instantaneous consumption models.

Apart from the above research, the following studies are also notable addressing the joint control problem from different perspectives. Liang *et al.* (2020) proposed an equitable control framework with connected vehicles by constraining the maximum delay experienced by any individual vehicle. Ding *et al.* (2021) adopted the MILP modeling approach to investigate the merits of dynamic lane usage in a CAV environment. This study sought to improve the intersection performance from the space domain. On the contrary, Ma *et al.* (2022) proposed to use dedicated lanes for CAVs but with shared phases, which can be considered an effort from the time domain. From a rare but precious approach, Liu *et al.* (2021) conducted field experiments to evaluate the intersection performance enhanced by signal optimization and CAV trajectory planning. The results report a considerable reduction in energy consumption and improvement in average travel speed.

3.2 Autonomous intersection management

AIM refers to the control strategy that the function of physical traffic signals in resolving conflicts is replaced by smart vehicles, such as CAVs, that are able to communicate with and follow the guidelines of infrastructures (Chen *et al.*, 2020; Guillen-Perez and Cano, 2022; Lee and Park, 2012; Lu *et al.*, 2022; Olovsson *et al.*, 2022). For this topic, we present two prevailing streams of research: reservation-based strategy; optimization-based strategy.

The very first study of reservation-based AIM can date back to the paper from Dresner and Stone (2004). In this pioneering work, the intersection area (the conflict zone in Figure 1) is divided into a number of homogenous cells, and each vehicle will send a request of those cells, including also other traversing information such as arrival time, velocity, direction, vehicle size and acceleration rates. A rule shall then be designed to accept and reject reservation requests from different vehicles. The majority of research in this area is centered on the development of new reservation rules.

The most natural and probably most widely used reservation rule is first-come-first-serve (FCFS), an intuitive rule inherited from queue theory. However, it has been well recognized that FCFS can sometimes be less efficient than traffic signals, especially under high traffic demand (Levin *et al.*, 2016). On this topic, Yu *et al.* (2019) provided a theoretical foundation for the capacity and delay estimation for autonomous intersections with the FCFS strategy. In their research, the AIM system is modeled as a M/G/1 queueing system with Poisson arrivals. The system performance of both vehicle-based FCFS and batch-based FCFS strategies was mathematically modeled with analytical formulations. The theoretical analysis indicated that although batch-based strategy outperforms the vehicle-based counterpart due to the advantages of platooning, it is inherently still a FCFS strategy and thus can be out formed by traffic signals because of the myopic nature of FCFS in system organization. Thus, in state-of-the-art research, FCFS is only used as a benchmark. For example, Li *et al.* (2019) proposed a priority-based algorithm that fixed the priority level of existing vehicles but kept updating the priority level of upcoming vehicles, so that latter coming CAVs can potentially be discharged first, violating the FCFS law. This simple change of reservation policy brought significant improvement in the intersection efficiency. Lukose *et al.* (2019) incorporated the operational patterns and insights of traffic signals into the development of reservation laws, which led to two new policies, namely, WEIGHTED and PHASED. Mitrovic *et al.* (2020) combined the alternative-direction lane concept with reservation-based intersection control, which resulted in superior performance compared to conventional fixed-time control plan and fully reservation-based intersection control strategy.

In reservation-based strategies, the conflicts within the intersection area are resolved with a rule-based approach largely by shifting the existing vehicle trajectories in time and space. On the contrary, optimization-based methods consider CAV trajectories as decision variables to eliminate conflicts proactively. For instance, Yu *et al.* (2019) developed an optimization-based control framework for autonomous intersection management. In the proposed model, CAVs either drive at the speed limit or follow the Newell's model when blocked by a preceding vehicle. To further simplify the computation, it is also assumed that CAVs follow deterministic trajectories in the conflict zone (Figure 1). Li *et al.* (2019) developed a similar optimization model with adjustable speed. To resolve the extra computation burden, a meta-heuristic Tabu search algorithm is applied to solve the optimization problem.

Considering the enormous number of decision variables and high requirement of control granularity, optimization problems in AIM feature high computation complexity. To this end, distributed control methods are drawing increasing attention. Mirheli *et al.* (2019) proposed a consensus-based control logic for the movement of CAVs in an AIM scenario. The objective is to minimize CAV travel time while avoiding near-crash conditions. Instead of using one large MILP, their research developed mixed-integer non-linear programs for each vehicle in a distributed fashion. To address the potential conflicts, vehicle consensus was realized through an iterative process to yield conflict-free trajectories that minimize the overall travel time. This framework fundamentally enabled real-time implementation due to the considerably reduced computation complexity, while only having a marginal objective value of 2.3% compared to centralized control methods. Wu *et al.* (2019) modeled the AIM problem as a multi-agent MDP, in which CAVs collaboratively minimize the intersection delay while avoiding conflicts. The complexity issue is largely addressed by the independent structures of the proposed algorithm, and conflicts are prevented by iteratively adapting coordination needs. Yao and Li (2020) investigated the AIM problem in a single-lane scenario with mixed traffic flows, where each vehicle aimed to minimize its own travel time, safety risks and energy consumption.

4. Conclusion and discussion

In this paper, we reviewed the two main categories of research regarding the opportunities and challenges brought by CAVs in isolated intersection management. The first category concerns CAV trajectory planning at an isolated intersection. In single-lane scenarios, control theory is arguably the predominant modeling framework and has been continuously exploited in CAV trajectory planning. At multi-lane intersections, due to the added complexity and uncertainties from lane changings, existing studies prioritize the fast completion of trajectory planning and execution so that lane changes can be completed before arriving at the stop line. This calls for either a computationally efficient algorithm or an optimal solution. Unfortunately, fast and also optimal solution has been rarely seen due to the curse of dimensionality. The second category is focused on the joint control and optimization problem of CAVs and the intersection, where the problem becomes even more complex. Regardless of the existence of physical traffic signals, mathematical programming models, distributed frameworks and machine learning techniques stand out to be the most prevailing and best-performing tools.

It is intractable to summarize the technical limitations for all of the ever-growing research papers, as each uses different setups, various assumptions and diverse objective functions. However, when reviewing the above papers, one common barrier stands out, i.e. the lack of benchmarks. Albeit with the booming development in this area of research, widely recognized benchmarks such as those in operations research and computer science are absent. The absence of such standards hinders the judgment of truly cutting-edge research, especially when it comes to the evaluation of computational performance and solution quality, two of the most fundamental and crucial metrics in this area. Specifically, many existing studies present the absolute computation time of case studies without theoretical computation complexity analysis. However, the absolute computation time depends on a number of factors, such as computing device and coding skills, and thus cannot always accurately reflect the algorithm complexity. In addition, the majority of existing studies compare their models to very basic models such as FCFS strategies and fixed-time intersection control but rarely with state-of-the-art models, probably because of the difficulties encountered during reproducing others' work. As stated by Zheng (2021), promoting reproducible transportation research might be a solution to remove the above barriers and thus should be where future efforts are devoted to.

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