A Survey on Intersection Management of Connected Autonomous Vehicles

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Intersection management of Connected Autonomous Vehicles (CAVs) has the potential to improve safety and mobility. CAVs approaching an intersection can exchange information with the infrastructure or each other to schedule their cross times. By avoiding unnecessary stops, scheduling CAVs can increase traffic throughput, reduce energy consumption, and most importantly, minimize the number of accidents that happen in intersection areas due to human errors. We study existing intersection management approaches from following key perspectives: 1) intersection management interface, 2) scheduling policy, 3) existing wireless technologies 4) existing vehicle models used by researchers and their impact, 5) conflict detection, 6) extension to multi-intersection management, 7) challenges of supporting human-driven vehicles, 8) safety and robustness required for real-life deployment, 9) graceful degradation and recovery for emergency scenarios, 10) security concerns and attack models, and 11) evaluation methods. We then discuss the effectiveness and limitations of each approach with respect to the aforementioned aspects and conclude with a discussion on trade-offs and further research directions.

Additional Key Words and Phrases: Connected Autonomous Vehicles, Traffic Intersection Management

1 INTRODUCTION

Intelligent Transportation Systems (ITS) have the potential to revolutionize transportation by providing safer and more efficient driving experiences. In the past decade, many automotive industries were focused on improving the Advanced driver-assistance systems (ADAS) and have tried to pave the road to deploy fully Autonomous Vehicles (AVs) that can drive without human intervention. Today, more than 65 automotive companies are permitted to test their AVs on the streets of California, US [35].

When AVs become connected, they can share their information with other AVs and/or the infrastructure in order to avoid potential accidents and increase the throughput of the roads. Traffic management of Connected Autonomous Vehicles (CAVs) can take place at different places and for different purposes including but not limited to platooning in highways, cooperative merging at ramps, automated roundabout management, cooperative lane changing at highways and automated intersection management. In this survey, we specifically focus on the management of CAVs at a signal-free intersection. In Figure 1, we have provided a high-level overview of automated intersection management with respect to other research topics to specify the scope of this survey.

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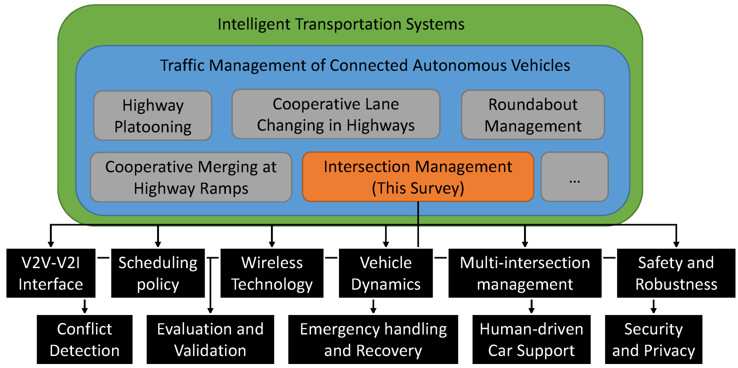


Fig. 1. Scope of this survey with respect to other research topics in the intelligent transportation system domain.

According to the Federal Highway Administration (FHA), 40 percent of all crashes involve intersections which account for the second-largest category of accidents[5]. CAVs approaching the intersection can exchange information with the Intersection Manager (IM) or other CAVs to reserve their cross time. As a result, automated intersection management can significantly reduce fuel consumption and travel time of the vehicles. In addition, accidents at an intersection that are caused by human errors e.g. red light runner can be minimized or even fully eliminated.

In the past few years, the intersection management of CAVs has been the focus of many researchers and so far, a variety of intersection management approaches [41, 68, 74] were proposed. Existing works on intersection management of CAVs can be categorized as distributed approaches and centralized approaches wherein distributed approaches CAVs communicate with each other over a wireless network to come up with a plan while in centralized ones, CAVs communicate with the infrastructure to receive a plan for crossing. Although automated intersection management is appealing, it will not be deployed in the real world unless it is proved to be safe, secure.

In the past few years, a number of surveys have been published which discuss existing works on intersection management of AVs and CAVs at signalized and non-signalized intersection. In 2015, Chen *et al.* [31] published the first survey on cooperative intersection management of vehicles and they studied existing methods for both signalized and non-signalized intersections. Since 2015 there have been more than 65 papers that are published in this area [95]. In a more recent survey[106], researchers summarized existing methods for coordination of CAVs at intersections and highway ramp-meters. This survey mostly studies existing works from the scheduling policy point of view and does not consider other aspects of intersection management of CAVs. In another study[72], Krishnan *et al.* categorized existing approaches to manage an intersection of CAVs. They have presented an analysis of existing techniques and compared their pros and cons. This paper, however, considers only 6 existing works and therefore is not complete. The most recent survey (published in 2019) [95] categorizes existing works on intersection management of CAVs at signalized and non-signalized intersections. This paper, however, is a non-technical survey as it categorizes existing works based on the country at which the research group resides, the year the paper is published, and the main objective of the paper (efficiency, safety, passenger comfort, etc.).

In this paper, we particularly focus on existing works on the intersections management of CAVs and so far, we were able to find 122 papers. Completing existing studies, we provide a thorough survey on existing works that are reported in the literature to date and evaluate them from following perspectives: 1) V2V/V2I interface for intersection management, 2) scheduling policy for CAVs, 3) wireless technology, 4) model for vehicle dynamics, 5) conflict detection, 6) extension to multi-intersections, 7) support for human-driven vehicles, 8) safety and robustness, 9) emergency situations and recovery, 10) security concerns, and 11) evaluation method. We highlight the limitation/superiority of each technique in addressing the challenges of deploying an intersection management technique and finally, we discuss the challenges that are left open to be addressed in the future.

The organization of the article is as follows: In section 2, the interface for V2V/V2I-based intersection management is studied. Section 3 present existing models used for estimating the behavior of vehicles. In Section 4, we discuss how conflicts are modeled at an intersection. The scheduling policy of intersection management is discussed in section 5. In section 6, we discuss existing wireless communication protocols. In section 7, we dig into multi-intersection management approaches. Compatibility with human-driven vehicles is discussed in section 8. Safety and robustness aspects of the intersection are examined in section 9. In section 10, we compare existing works from recovery and graceful degradation point of view, and in section 11, we explore security threats to the intersection management system. We also compare existing works from the evaluation method perspective in section 12.

2 V2I/V2V INTERFACE FOR INTERSECTION MANAGEMENT

Deployment of an intersection management algorithm in real life requires certain specifications to be defined by designers. For instance, the algorithm must specify what information will be exchanged, who is responsible for the scheduling of CAVs -is there a separate infrastructure near the intersection or will one of the CAVs take the responsibility?

Existing decentralized/centralized approaches are different in terms of communication protocol and information that is shared. Some of the existing works specifically mention what information needs to be exchanged while some other works, do not and assume that a CAVs or the Intersection Manager (IM) have to access to all information of CAVs.

Based on the fact that who manages the intersection, we categorize existing works into two groups: 1) Distributed, where CAVs do the scheduling themselves and 2) Centralized, where there is a station near the intersection that schedules approaching CAVs. Figure 2 shows an overview of a centralized and distributed intersection management interface.

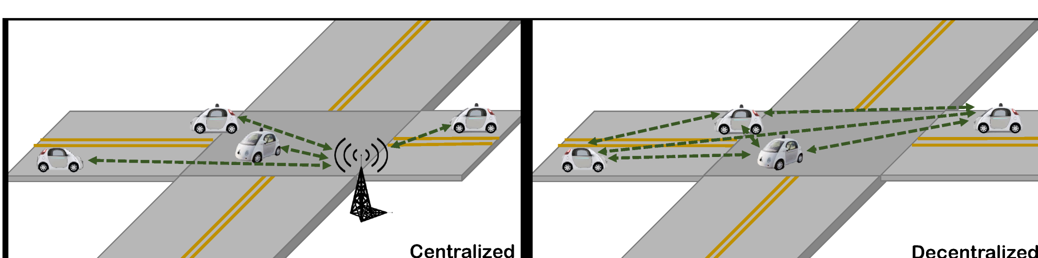


Fig. 2. Main interfaces to manage the intersection of CAVs. In centralized approaches, CAVs communicate with the infrastructure while in distributed approaches, CAVs communicate with each other.

2.1 Distributed Approaches

As an advantage of distributed approaches, they do not need support from infrastructure, which means they can scale easily and be used in uncrowded intersections controlled by stop signs and those in rural areas.

Li *et al.* [76] developed a distributed intersection management algorithm where CAVs randomly communicate with each other to form small groups when they are within a certain radius of the intersection. All CAVs share their ID, width and length, incoming/outgoing lane, velocity, and position. Then, CAVs from different groups communicate with each other to collect the information of CAVs in other groups. As soon as a CAV receives the information of all vehicles, it becomes the leader or intersection manager and schedules the cross-time of CAVs. The leader also lets other CAVs know about its leadership so that they stop collecting data.

STIP (Spatio-Temporal Intersection Protocol) [15] is another cooperative intersection management algorithm where there are three message types that a CAV sends to the others: ENTER, CROSS, and EXIT. In this method, CAVs share their ID, current road segment, current lane, future road segment, arrival-time, exit-time, list of trajectories, list of arrival times, and message sequence. When two CAVs intend to cross the same zone and their cross-time overlaps, the CAV with higher priority continues and enters the intersection while the CAV with lower priority slows down and stops before entering the conflict zones. The priority for CAVs is determined based on the FCFS policy where a CAV with earlier arrival time has a higher priority.

In [64, 65], Katriniok *et al.* proposed a model predictive control (MPC) technique to coordinate vehicles through the intersection. Upon approaching the intersection, each CAV receives the trajectories of all other CAVs and then formulates and solves an optimal control problem to find a sequence of actions. Next, the CAV broadcasts its information including distances to collision point with other CAVs. This process is repeated again after a short time-step to handle newly approaching CAVs.

Aoki *et al.* [9] proposed a general solution for scenarios that a pair of CAVs have conflicts on their future paths including an intersection. In this work, a Request-response negotiation-based protocol is proposed to detect dynamic intersections of CAVs. CAVs notify each other about the existence of conflicts and yielding to/interrupting other CAVs. In this approach, four message types are defined: 1) Dynamic Intersection or DI request, to notify other CAVs, 2) DI approve, to acknowledge the requested maneuver, 3) DI interrupt, to ask other vehicles to stop, and 4) DI yield, to respond to DI interrupt.

In [83], the intersection area is divided into multiple conflict zones. Upon approaching the intersection, each CAV periodically broadcasts its arrival time and departure time with respect to all the conflict zones that it intends to occupy. If a CAV detects a conflict, it determines if it has the advantage to enter the conflict zone first. A CAV will have the advantage if it proposes to 1) leave some conflict zone later than the other CAV, 2) leave all conflict zones earlier than the other CAV, and 3) enter some conflict zone earlier than the other CAV. The vehicle that has the advantage continues with its plan and the other CAV changes its plan such that its enter time to all conflict zones is later than the exit time of the CAV with the advantage. This technique assumes that all CAVs are synchronized where the computation happens at the same time within the broadcasting period

Belkhouche *et al.* propose a distributed collision detection system [22] that is aware of the unsafe situations that may happen with respect to another CAVs that is approaching the intersection. In this approach, the set of all velocities that may cause an accident in the future are determined for a pair of CAVs. If a conflict exists, one of the CAVs must accelerate and the other one will decelerate. The optimal crossing is then determined by finding the desired velocity for both CAVs such that CAVs change their velocity minimally while avoiding the set of unsafe velocities.

In Bian *et al.* approach[25], the area before entering the intersection is divided into three zones. A CAV will first enter the observation zone, where it observes the current state of other CAVs and their order, then it enters the optimization zone, where it optimizes its trajectory, finally, it enters the control zone, where the CAV tracks the desired trajectory. This paper assumes that the communication range is limited and therefore a CAV may not be able to receive the information of all CAVs. As a result, it estimates the state (position and velocity) of out-of-range CAVs using the information broadcast by their neighbors.

In [51], CAVs send/receive position, speed, and direction upon entering the communication area and then calculate a priority based on the arrival time. A CAV with lower priority yields to CAVs with higher priorities by slowing down such that it arrives at the intersection when the intersection is cleared. This process is repeated until a CAV leaves the intersection.

Among existing works that propose a distributed intersection management interface, in [76], a leader is selected dynamically to schedule CAVs while in the rest[9, 15, 22, 64, 83], each CAV determines its plan based on the shared information of other CAVs and its own state. Selecting a leader that performs intersection management is very similar to a centralized approach. Later, we will study the pros and cons of centralized and distributed intersection management. In general, each distributed approach follows a unique protocol for communication where the number of exchanged messages and their size differs.

2.2 Centralized Approaches

Centralized algorithms mostly follow a server-client scheme where vehicles send a request to the IM and the IM replies with a response. We categorize existing centralized approaches into two groups: query-based intersection management or QB-IM, and assignment-based intersection management AB-IM approaches. In QB-IM, vehicles query a safe passage from the IM by proposing a cross-time/velocity and the IM either accepts or rejects the vehicle's proposal. In AB-IM, vehicles share their status with the IM and the IM assigns a cross-time to each vehicle, and vehicles follow that.

2.2.1 Query-based Intersection Management. Autonomous Intersection Management (AIM) [41] was one of the initial attempts to develop a centralized algorithm for intersection management of CAVs. In AIM, the intersection is modeled as a grid of squares. Each of these squares is represented in discrete time-steps. Vehicles approaching the intersection query safe entry to the intersection by sending their estimated time of arrival and velocity of arrival. The IM generates the future trajectory of the vehicle in terms of time-space (which square will be used and when) and checks if it conflicts with other time-space reservations (for other vehicles). If there is a conflict, the IM rejects the request and the vehicle slows down and requests again after a timeout. If no reservation is assigned to a vehicle, it will stop behind the intersection edge and request again. If there is no conflict, the vehicle continues and enters the intersection. AIM is a query-based intersection management (QB-IM) approach where vehicles query safe passage from the IM and the IM replies a YES/NO. As a result, this approach may face higher network overheads and achieve lower throughputs. This is because vehicles may come to a complete stop and have to send multiple requests until getting a reservation. [82] proposes a similar QB-IM methodology where vehicles send a request to the IM reporting their future conflict zone occupation time (CZOT). The IM store CZOTs of all vehicles and share it with all vehicles. Then, each vehicle finds a valid solution (a new CZOT that does not have any conflict with other CAVs) and reports it to the IM. If two CAVs request the CZOT at the same time, the IM responds to them in the order it receives the request. IM does not respond to other CAVs until it receives the proposed CZOT and updates its local CZOT [34] is also a similar query-based algorithm where each CAV sends a reservation to the IM and IM either accepts or rejects the request. In this approach, there are two zones, 1) queuing zone and 2) acceleration zone. The vehicle sends their request only when they are in the queuing zone.

Jin *et al.* [62] follow another approach where platoons of CAVs are formed using V2V communication and each platoon has a leader. The leader communicates with the IM on behalf of its platoon by sending the platoon's earliest arrival time and passage time. The IM evaluates the reservation time slot and responds to the proposal of the leader by either accepting or rejecting the request and suggesting a reservation for the platoon. [19] and [18] are similar approaches where platoons of CAVs are formed and only leaders communicate with the IM by sending one the following messages: 1) Request, 2) Change-Request, 3) Acknowledge or 4) Done. Accordingly, IM follows a query-based approach and responds to a request by sending one the following messages: 1) Acknowledge, 2) Confirm, or 3) Reject. For the request, a leader vehicle sends its VIN (vehicle identification number) as ID, current position, velocity, acceleration, estimation for the time of arrival, and the size of the platoon. [60] is another QB-IM approach where vehicles send their estimated earliest arrival time to the IM to reserve a time slot. The IM uses a dynamic reservation system that accepts or rejects a request based on the priority of the request. [61] is a variation of the same approach using a different scheduling policy and [24] proposes to use a similar QB-IM approach.

2.2.2 Assignment-based Intersection Management. In 2016, Yang *et al.* [127] proposed an AB-IM algorithm where the IM collects information of all CAVs that are within the range of the intersection and assigns a trajectory to each vehicle. The scheduling process is repeated when a new vehicle enters the control zone, an existing vehicle departs the intersection or it comes to a stop.

Crossroads [8] and Crossroads+ [67] are similar AB-IM approaches where vehicles first synchronize their internal clock with the IM and then, let the IM know of their presence by sending their position, velocity, and exit lane along with a timestamp that corresponds to the captured status. IM checks the status of existing vehicles and assigns a constant velocity and "time to actuate" to each vehicle. Once a vehicle receives the response, waits until the time to actuate and then accelerate/decelerate to maintain the assigned velocity. Azimi *et al.* [14] propose a similar approach where the IM assigns a TOA and VOA to a CAV and also checks for deadlock and resolve them. In [108], another AB-IM approach is presented where approaching vehicles send a request to the IM containing their utility function (u) and safety function (s) and the IM schedules vehicle such that the sum of all utility functions is maximized. Authors have also provided a mechanism for truthful utility reporting. In Lu *et al.* approach[85], the IM creates a queue for approaching CAVs which is sorted based on the request time and then, assigns an occupancy in space-time to CAVs. Qian *et al.* [103] present an interface between the IM and CAVs where each CAV sends a request by sharing its information and the IM computes a scheduling solution for it. The IM also waits for feedback from the CAV to make sure the scheduled plan is received. In [68], each CAV sends its position, velocity, outgoing lane, and timestamp to the IM and the IM assigns a time of arrival and velocity of arrival to the CAV.

We have categorized existing works in terms of their interface and management algorithm in Table 1.

Intersection management interface		
Distributed	Centralized	
	Query-based	Assignment-based
[9, 15, 22, 25, 44, 51, 64, 65, 75, 76, 83, 104, 133]	[34, 41, 60, 61, 80, 115, 120]	[8, 14, 18, 33, 43, 62, 67, 68, 85, 86, 103, 108, 109, 112, 127]

Table 1. Existing Intersection management algorithms based on the proposed interface for communication among vehicles (or with intersection manager).

In QB-IM, the IM either accepts or rejects a request, while in AB-IM, IM explicitly assigns a reservation to the CAV. As a result, AB-IM algorithms can achieve higher throughputs compared to

QB-IM ones but the processing time of the intersection manager for an AB-IM algorithm is more than a QB-IM.

Both centralized and distributed approaches have their own pros and cons but most importantly, in centralized approaches, the IM is a single point of failure and therefore less reliable compared to distributed approaches. Also, distributed approaches are more scalable since they don't require support from infrastructure and can be deployed at every intersection. In centralized approaches, CAV's control is given to the IM once it enters the intersection zone and given back to the CAV when it leaves the intersection area. On the other hand, CAVs need to broadcast their information periodically to let newly arrived CAVs know of their cross time, while in centralized techniques, IM stores the information about the state of the intersection (e.g. occupancy times-areas) and therefore, CAVs do not have to broadcast their information periodically. As a result, distributed techniques may have higher network overheads compared to centralized ones. Time synchronization is a fundamental part of the intersection management which has received less attention. Almost all centralized and distributed approaches require having the same notion of among all nodes in order to ensure the correctness of the intersection management and safety of CAVs. Since all CAVs are equipped with GPS receivers, they can maintain an accurate notion of time up to few microseconds. However, if GPS signals are poor/not available in an area, time synchronization should be a part of the intersection management's V2V/V2I interface.

3 VEHICLE DYNAMICS

Typically, a model is needed to estimate/predict future trajectories of vehicles before and at the intersection. In the literature, researchers have considered different models for vehicle dynamics. Some existing works use a simple one-dimension model, while some use more complex models. Next, we will study some of the models that are used for the dynamics of vehicles. Figure 3 shows different approaches used to model the dynamics of a vehicle in existing works on intersection management of CAVs.

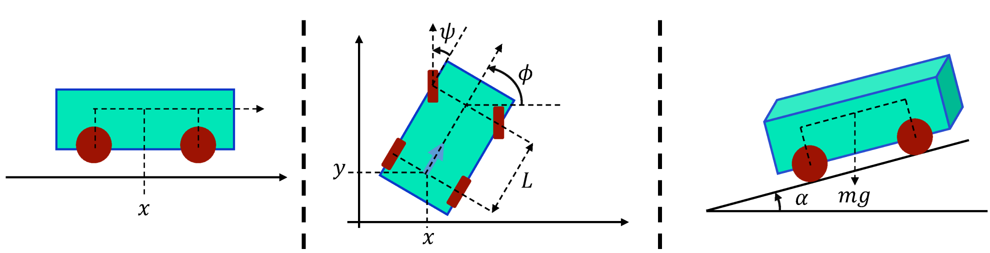


Fig. 3. (a) Double integrator model - considering the longitudinal movements of the CAV only (b) 2D model - considering longitudinal and lateral movements of the CAV (c) High-fidelity model - considering the road slope and aerodynamic drag force (F_d).

3.0.1 one-dimension Model (Double integrator). This model considers the longitudinal movements of the vehicle only.

$$\begin{cases} \dot{x} = v \\ \dot{v} = u \end{cases} \tag{1}$$

x and v are the longitudinal position and velocity of the vehicle and u is the input to the vehicle that captures the input to the throttle and brake for positive and negative inputs respectively.

3.0.2 4-wheel Model. This model considers both the longitudinal and latitudinal movements of the vehicle [41]:

$$\begin{cases} \dot{x} = v\cos(\phi) \\ \dot{y} = v\sin(\phi) \\ \dot{\phi} = \frac{v}{L}\tan(\psi) \\ \dot{v} = u \end{cases} \tag{2}$$

x and y are the longitudinal and latitudinal position of the vehicle in Cartesian coordinate. v is the absolute velocity of the vehicle and u is the input to the vehicle that captures the input to the throttle and brake for positive and negative inputs respectively. ϕ is the heading angle of the car, ψ is the steering angle of the vehicle and L is the wheelbase distance.

3.0.3 Bicycle model. This is a simplified version of the 4-wheel model which is created by projecting front and rear wheels onto two virtual wheels located at the middle of the car. The vehicle dynamics for the bicycle model can be written as:

$$\begin{cases} \dot{x} = v_x cos(\theta) - v_y sin(\theta) \\ \dot{y} = v_x sin(\theta) + v_y cos(\theta) \\ \dot{\theta} = r \end{cases} \tag{3}$$

where v_x and v_y are the longitudinal and lateral velocities of the vehicle respectively and r is the yaw rate.

3.0.4 Modeling Air Drift, Road Slope, and Mass. This model considers the effect of air drag force and road slope in the vehicle model[25].

$$\begin{cases} \dot{x} = v \\ \dot{v} = \frac{\eta}{mr}T - \frac{C_A}{m}v^2 - g\big(\sin(\alpha) - f\cos(\alpha)\big) \end{cases} \tag{4}$$

where T is the torque applied to wheels, η is the mechanical efficiency of the driveline, m the mass r is the tire radius, C_A is aerodynamic drag coefficient, f is the rolling resistance, g is the gravitational acceleration and α is the road slop.

We have categorized existing works on intersection management of CAVs based on the considered model for the vehicle dynamics.

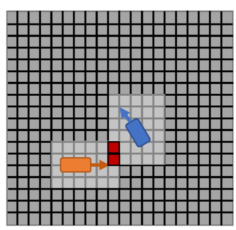
1D model (Double integrator)	2D model (4-wheel vehicle)	Considering mass, air drift, and road slope
[11, 36, 47, 48, 50, 51, 54, 56, 57, 63–65, 69, 70, 74–77, 80, 84, 87–90, 92, 94, 96, 98, 112, 113, 122, 127–131, 133]	[8, 41, 46, 55, 67, 68]	[19, 25, 26]

Table 2. Existing works on intersection management of CAVs categorized by the considered vehicle dynamics

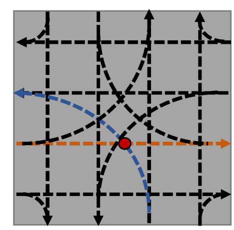
The double integrator model is linear and therefore is easy to work with because the solution for the behavior can be determined analytically. However, it does not capture the movement of the vehicle in 2D space. To model the behavior of a CAV even more accurately, different factors like air drift, mass, friction, road slope can be considered. However, considering a high-fidelity model will put a burden on the scheduling system since more computation is needed to estimate the behavior of the CAVs and determine a feasible solution –especially in optimization-based approaches. As a result, it remains an open problem to determine the right level of fidelity. There are many parameters that should be considered to model the actual behavior of a CAV where some of them are variable e.g. road slope, wind, the mass of the vehicle, road friction coefficient, etc. Therefore, accurate prediction of the behavior of a CAV requires an online identification mechanism to estimate such parameters.

4 CONFLICT DETECTION

In order to detect a possible conflict that two CAVs may have at the intersection, existing works have proposed two approaches: 1) considering a Spatio-temporal occupancy map for the intersection area and 2) considering the expected trajectories of CAVs inside the intersection.



(a) The grid represents the areas that will be occupied by vehicles at time t. A conflict exists if two areas have an overlap (depicted in red).



(b) Predefined paths are defined for crossing the intersection. A conflict exist if two paths cross and the cross times of the vehicles overlap.

Fig. 4. Modeling a conflict at the intersection.

The first approach models the intersection as a grid of conflict areas and the path of a CAV inside the intersection is captured by indicating which blocks (of the grid) will be occupied by a CAV at each time-step. In this approach, the intersection management algorithm needs to make sure two CAVs are not scheduled to occupy a block at the same time. The granularity of splitting the intersection area into a grid varies among different approaches. In the extreme case, the whole intersection area is considered as a conflict area.

In the second approach, there is no need to store the occupancy map for the whole intersection area, instead, the expected path of two CAVs is used to determine the location at which two CAVs may have a conflict. This can be done offline as the expected paths of CAVs are known e.g. for going straight or making a turn.

We have categorized existing works in terms of the way conflicts are modeled in Table 3.

Conflict Detection using Occupancy Map	Conflict Detection using on CAVs' Trajectory
[8, 9, 14, 15, 22–25, 34, 41, 49, 51, 60, 62, 69, 76, 82, 83, 85, 101, 103, 104, 108]	[64, 65, 67, 68, 85, 127]

Table 3. Categorizing existing works in terms of modeling the conflicts inside the intersection area.

Using an occupancy grid to model conflicts is computationally cheap since it involves simple boolean checking operation, however, the computation increases by considering finer conflict zones and smaller time-steps. The throughput of the intersection is directly dependent on the granularity of the Spatio-temporal grid and generally finer grids can achieve higher throughputs.

5 SCHEDULING POLICY

The main purpose of intersection management is achieving higher throughputs compared to conventional traffic lights while ensuring the safety of vehicles. In this paper, the process of deciding which CAV should cross the intersection first and which CAV should cross second and so on is called "scheduling". We group existing scheduling policies into three main categories: i) First-Come First-Served, ii) Heuristic, and iii) Optimization-based. Figure 5 shows an example of an intersection and possible solutions determined using the FCFS, optimization-based and a heuristic approach.

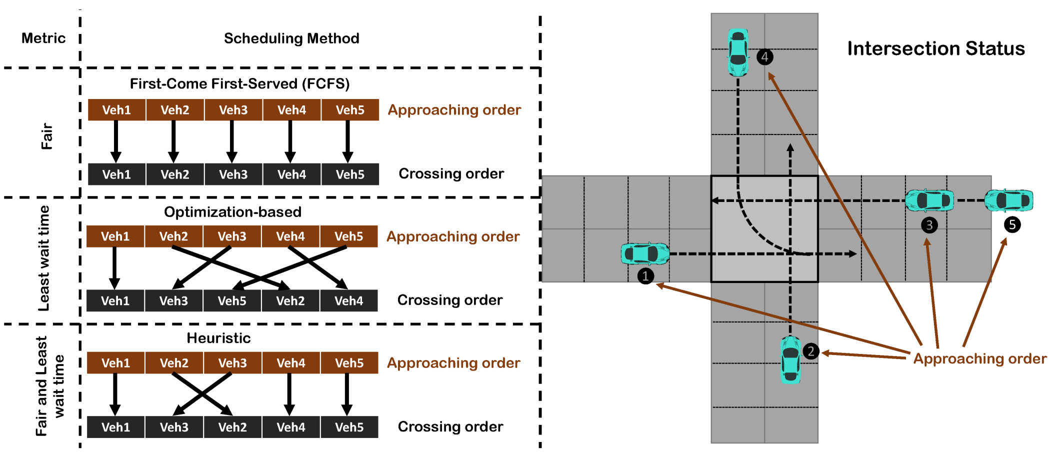


Fig. 5. Examples of FCFS, optimization-based and heuristic scheduling policies. In the left section, the approaching and crossing order of vehicles is indicated. In the right section, the status of the intersection at the scheduling time is depicted.

5.1 First-Come First-Served Approaches

First Come First Served (FCFS) traffic control algorithms works as the name sounds, the first vehicle to arrive is the first vehicle to be served and grants entry to the intersection. One of the first implementations of an FCFS method is AIM which was proposed by Dresner *et al.* [41]. Requests to the intersection manager are processed in the same order they are received. For scheduling the cross of a vehicle, AIM stores a reservation grid for the area of the intersection. This segmentation can be used to check if another vehicle is occupying the space at a time. FCFS was the scheduling policy for many other intersection management techniques. For instance, [15] considers a reservation map with smaller segmentation, [23], [69] and [104] similarly consider a reservation area for the intersection, [43] uses a predefined conflict table between entry lanes of the CAVs and a locking mechanism, and [68], [8] and [67] use predefined trajectories of the vehicles inside the intersection for reservation. In [62], Jin *et al.* proposed to use FCFS for platoons of CAVs instead of individual vehicles where the IM uses a reservation table to schedule the next platoon. In [51], a priority value is calculated for each CAV based on the arrival time and the priority specifies the crossing order of CAVs. Lu [85] *et al.* is another FCFS approach that a queue of CAVs is created and the intersection manager serves the top CAV in the queue by assigning a time slot.

5.2 Optimization-based Approaches

Despite FCFS scheduling methods, optimization-based approaches try to minimize the average travel time of the whole intersection regardless of their approaching order. As a result, the crossing order of vehicles may vary from the approaching order of vehicles.

There have been several optimization-based approaches that solve the intersection management scheduling problem. The simplest type of optimization-based scheduling is done by controlling the status of the traffic light namely Signal Phase, and Timing (SPaT) to achieve a high throughput [25, 45, 48, 49, 84, 101, 126]. In such approaches, the IM suggests an optimal trajectory for the CAVs to follow such that they will hit a green light. [48] and [49] use Mixed Integer Linear Programming (MILP) to solve the optimization problem and [10], extends it to a grid of connected intersections.

Researchers have also proposed optimization-based approaches for an intersection without a traffic light. Generally, the goal is to increase the throughput which is formulated as minimizing the travel time/wait time/cross-time [26, 53, 59, 74, 80, 133]. To avoid a collision in the intersection area, a set of constraints are defined based on the unsafe states e.g. two vehicles be very close to each other at any time. [59] uses a POMDP (partially observable Markov decision process) to model vehicle dynamics and the Adaptive Belief Tree (ABT) algorithm for finding the optimal solution. Xu *et al.* approach [126], similarly creates a tree for all the possible solutions for the passing order where the leaf of the tree represents the complete solution.

Guler *et al.* [54] proposed an iterative algorithm to find the optimal arrival/departure sequence of CAVs. In [127], they extended their work and formulated the intersection management problem using two optimization problems: 1) finding the optimal arrival/departure sequence of CAVs, and 2) finding the optimal trajectory of each vehicle once arrival/departure times are known. They propose to use the Branch-and-Bound approach to find the optimal arrival/departure sequence. [55] also solves an optimization problem to minimize the delay of CAVs. This paper employs the particle swarm optimization (PSO) algorithm to find the optimal solution. Lu *et al.* [86] solve the optimization problem using MILP to minimize the travel time. Liu *et al.* [83] propose to convert a centralized optimization problem into distributed optimization problems that are solved locally on each vehicle to find the optimal solution. In [18], a platoon-based approach is introduced to find the optimal solution that yields minimum average delay. Similarly, Timmerman *et al.* [117] propose an optimization-based approach for platoons of vehicles. In [76], Li *et al.* proposed to create a tree where each node corresponds to a valid schedule. The optimal entrance of the vehicles is then determined by traversing the tree. [132] studies the problem of managing a grid of intersections where the traffic flow of each link should be determined. Linear programming is used to solve the problem. In [61], Jin *et al.* linearizes the optimization problem using the big M method and then, solves it using linear programming to find the minimum travel time of vehicles. [98] uses a fourth-order Laplace model for vehicle dynamics and use the multi-objective fuzzy rule-based system to find the minimum travel time of vehicles. In all aforementioned approaches, a goal function was defined based on the travel time of the vehicles and dynamics of the vehicle, and safety specifications were modeled as constraints.

There are other approaches that consider velocity variation [63–65, 70, 90, 92, 94, 112], passenger discomfort [64, 94, 128], communication overhead [113], acceleration/deceleration variation [112], absolute acceleration/deceleration amount [56, 63, 70, 75, 112, 122, 129–131] and fuel consumption [57, 87, 122, 128] as a metric and define the goal function based on it. In [94], Murgovski *et al.* reformulate the optimization problem into a sub-problem by finding the optimal entrance order of vehicles and then transformed it into a convex problem. [130], [131], [129], [122] and [89] follow optimal control approaches and use the Euler-Lagrange equation to solve the optimization problem analytically. In [75], the optimization problem is solved in three steps using Active-set

Method (ASM), Sequential Quadratic Programming (SQP) and Genetic Algorithm (GA). Philippe *et al.*[100] propose to create a local utility function for each CAV that is a function of the inverse of distance every two CAV, the difference from the maximum velocity and difference from the initial velocity. Then, the Probability Collectives (PC) method is used to optimize the utility function. In [79], authors propose to use Discrete Forward-Rolling Optimal Control (DFROC) to minimize the total delay of CAVs.

5.3 Heuristic Scheduling Approaches

Heuristic approaches take another way to solve the intersection management problem that isn't guaranteed to be optimal but is sufficient for reaching the immediate goal. For instance, researchers from MIT have proposed a scheduling algorithm called BATCH[116] with a designating reordering period. When the IM receives a request it doesn't assign a velocity to the vehicle immediately. Instead, it waits for a designated time period and keeps the record of all requests. Once the period is over, it re-orders the entrance time of vehicles to get a better schedule. The most efficient pattern of entry is chosen. Stevanovic *et al.* proposed a quite different approach to manage the intersection through the re-arrangement of the typical lane configuration so that there are fewer conflicts in the roadway itself[114].

Another heuristic approach is a bidding system to resolve conflicts within CAVs [120]. Vehicles can bid currency to beat out other vehicles to get reservations for the intersection. In many cases, a vehicle has to pay for the reservation of vehicles in front of it too in order to clear the queue. Wei *et al.* [123] follow a game-theory approach to find a schedule that has the least conflicts. Another heuristic approach is proposed by Jin *et al.* [60] where a mixture of a priority-based and an FCFS is implemented, where vehicles with higher priorities are processed earlier. In a similar work, Elhenaway *et al.* [44] propose a game theory-based heuristic based on the chicken game, where vehicles approaching the intersection have a joint utility function associated with each action.

In [77], Li *et al.* proposed a similar approach where a reward function is defined based on two metrics: crossing the intersection in a timely manner, not hitting any vehicles, and keeping a reasonable distance from other vehicles. Makarem *et al.* [88] propose a method based on a local navigation function that takes into account a vehicle's size and ability to accelerate/decelerate quickly when being scheduled. [11] follows a heuristic approach, where the IM determines the highest possible velocity of arrival that a vehicle can achieve and then selects the schedule that yields the earliest time of arrival.

Aoki *et al.* [9] propose a heuristic approach that is created from the integration of the FCFS policy and a timeout policy. CAVs are normally served based on the FCFS but when the wait time of a CAV is greater than a threshold, it interrupts the operation of the intersection and lets the CAV with excessive wait time to pass. Wu *et al.* [125] proposed a reinforcement learning approach to figure out a policy that is collision-free. The Q-learning method was used to update the policy and intersection delay was used as the reward. In [22], Belkhouche *et al.* presented a heuristic approach that finds the best crossing order based on the safety margins defined for crossing without collision. Another heuristic scheduling approach is presented in [108] where vehicles report their utility function to the IM and the IM determines a schedule such that it maximizes the utility values of all vehicles while maintaining the fairness when possible. [28] and [36] look at the intersection management as a verification problem where the goal is to check if there exists an input that such that the system can avoid the set of *Bad States* or an unsafe situation. Wu *et al.* [124] propose to use the current best known local solution using the Ant Colony Optimization (ACO) approach to find the minimum wait time of vehicles. [34] proposes to create a Red-Black Tree from conflicts and then traverse the tree and find the earliest time that the slot is available. Buckman *et al.* [29] propose a modified version of FCFS to schedule CAVs where a negotiation occurs between CAVs in the form of pairwise swapping. They use Social Value Orientation (SVO) to create a utility function and a swap occurs only when the summation of utility functions is increased.

We have categorized existing works based on their scheduling policy in table 4.

FCFS	Optimization-based	Heuristic
[8, 15, 23, 40, 42, 43, 46, 51, 52, 58, 62, 68, 69, 85, 104, 105, 109, 110, 115]	[10, 18, 25, 26, 48, 49, 53–57, 59, 61, 63–65, 70, 74–76, 79, 80, 83, 84, 86, 89, 92, 94, 98, 112, 113, 122, 126, 127, 129–133]	[9, 11, 22, 28, 29, 34, 36, 44, 60, 77, 88, 108, 114, 116, 120, 123–125]

Table 4. Categorizing existing works based on their scheduling policy.

The scheduling policy of intersection management is directly related to the throughput of vehicles. In addition to throughput, fairness is a key metric in determining the scheduling policy because waiting for a long time may not be acceptable for most people. The FCFS algorithm fulfills the fairness requirement and vehicles will not wait for an improperly long time. However, FCFS may not be efficient and its performance degrades significantly as the intersection scales.

There is a tradeoff between fairness and the overall throughput that an approach achieves. We believe that both throughput and fairness are important metrics and should be taken into account for realistic implementations. On the contrary, a heuristic method can achieve better throughput compared to FCFS and all vehicles will eventually receive a reservation i.e. vehicle delay is bounded. Another disadvantage of optimization-based approaches is the delay due to the processing time of the intersection management for finding the optimal schedule, and it becomes worse as the intersection scales. On the other hand, analytical optimization-based approach and heuristic approaches can avoid this problem.

6 WIRELESS TECHNOLOGY

Vehicle to everything (V2X) is a family of communication technologies that are used for information sharing of vehicles with other vehicles (V2V), infrastructure (V2I), and pedestrian (V2P).

Currently, two types of wireless technologies exist for connected vehicles: i) DSRC (Dedicated Short-range Communication) [32] and 2) Cellular-V2X (C-V2X). DSRC uses 802.11p protocol at the physical layer [7] and its network architecture and security are defined by IEEE WAVE standards [78]. DSRC uses SAE J2735 [93] standards to define message format at the application layer and J2945/x [93] family of standards for defining performance requirements of different V2X scenarios. One of the important messages in DSRC is Basic Safety Message (BSM) [3], which is proposed to be used as a way to share information in some of the intersection management papers [9, 12, 13, 15, 16, 103]. It should be noted that most of the existing works do not specifically mention what wireless technology they propose to work.

C-V2X is a 3GPP communication technology [121] that works with the cellular network and has controlled Quality of Service (QoS) [118]. C-V2X has two modes of operation, cellular communication (Uu) and direct communication (PC5). Uu mode enables V2V communications through the cellular network while PC5 allows for direct communication among vehicles similar to DSRC. DSRC achieves low latencies and high reliability when a few vehicles are present, however, its performance deteriorates in a dense environment with many vehicles. C-V2X, on the other hand, has shown more reliable latencies even in dense environments. In terms of communication range, DSRC is more suitable for low-range communications, while C-V2X can provide long-range communications. Compared to C-V2X, DSRC has been tested more often due to its availability (from

2017) [107]. Since DSRC uses message broadcasting, it benefits from user anonymity but will be inefficient as point-to-point communication is not possible.

	DSRC	C-V2X
Pros	good hardware support, proved to work with J2735 messages, Anonymity of users	Long range communication support, can perform point-to-point communication
Cons	limited range, message are broadcast only, may not reliable in dense areas	limited hardware support

Table 5. Comparing DSRC with Cellar-V2X

Safety and efficiency of the intersection management depend on the latency, range, and rate of the communication protocol. Since Intersection management has safety-critical timing constraints, bounded time communication is needed to make sure messages are delivered to vehicles on time. The communication range also plays a significant role in the correctness of intersection management and can affect efficiency. Since CAVs cannot communicate with the infrastructure or each other until they are close enough to the intersection, they should drive at a slower speed to make sure when they receive the information for the first time, they have enough time to safely slow down or in the worst-case stop if needed. Given the total amount of data that each CAV needs to send and receive as well as the communication rate of the wireless technology is known, the maximum capacity of the intersection management can be determined in terms of the number of vehicles that can be present at the same time.

7 MANAGING MULTIPLE INTERSECTIONS

Since a city can be broken down into a grid of intersections, effective intersection management of CAVs is key to city-wide traffic management. Hausknecht *et al.* [58] extended the AIM approach[41] and proposed an intersection management policy for a grid of intersections. In this approach, the intersection manager estimates the delay of traffic using 4 features: i) the total number of active vehicles (TAV) that exists within the range of the intersections, ii) the total number of active vehicles along the planned path (PAV), iii) the previously calculated PAV (oPAV) in the last step, and iv) the average traversal time for the planned trajectory (TWA). The estimated traversal time of a vehicle is then calculated as:

$$T_{est.} = 0.09TAV + 0.83PAV + 0.25oPAV + 0.25TWA + 2.26 \tag{5}$$

The above equation is determined by simulating a single intersection and linear regression approach. Once the estimated traversal time is determined for each vehicle, an A* search is performed to find the best scheduling. The proposed algorithm is evaluated for a 2x2 grid of intersections.

In a similar work [81], the problem of CAV routing is solved using an iterative A*. There are 3 steps in each iteration, i) batch processing stage, where the data of CAVs are collected using simulation, ii) routing stage, where A* is used to find the best route for vehicles, and iii) congestion checking stage, where vehicles are re-routed to avoid congestion. This approach predicts future traffic flows using simulation. This approach is evaluated on different sizes of intersections up to 9x9 using SUMO. Their iterative algorithm has shown better results compared to AIM's multi-intersection management approach.

In another work, a market-inspired [120] approach is proposed to manage a network of intersections. The idea is that CAVs bid a price to get a reservation in order to drive through the intersections and intersection managers will follow an auction-based approach to provide the reservation to CAVs. A model is provided for CAV drivers which considers the time of travel in a free-flow scenario and the price of the travel governed by the intersection managers. This approach is evaluated in a mesoscopic-microscopic simulator.

In a recent work [122], authors propose a greedy algorithm to optimize the sequence for route planning in a grid of intersection.

Fine-grain information about the status (position, velocity, lane, route) of CAVs is more beneficial for intersection management compared to coarse-grain information like traffic flow. However, the processing of fine-grain information can be very compute-intensive and requires high-performance computing solutions.

8 HYBRID (HUMAN-CAV) INTERSECTIONS

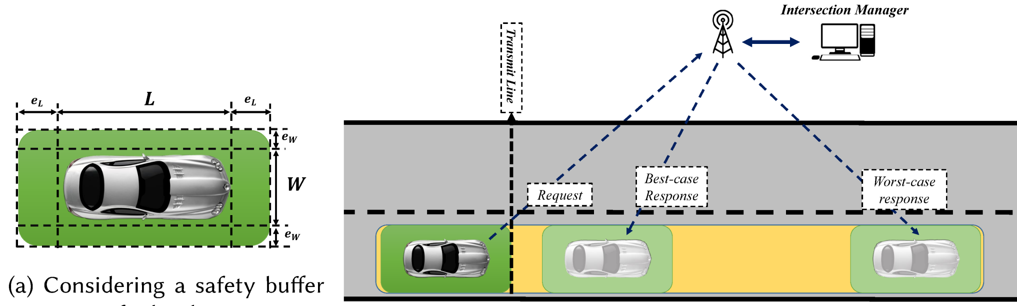
Deployment of a fully autonomous intersection of CAVs is still far from happening since it is unlikely to have an intersection exclusively for CAVs only. The intermediate step will have a mixture of human-driven vehicles (HVs) and CAVs, which we refer to as *hybrid intersections*.

One of the first attempts to consider a hybrid intersection was a part of the AIM approach [41]. Dresner and Stone proposed FCFS+Light, an intersection management mechanism that is integrated with a traffic light model. The intersection manager follows a query-based approach to assign the reservation to incoming CAVs and HVs will follow the normal traffic light rules. In a similar work, Sharon *et al.* proposed Hybrid-AIM (H-AIM) [110], which was built on FCFS+Light. The main difference between FCFS+Light and H-AIM is that in FCFS+Light, IM immediately rejects a reservation request that is received from a CAV if the light is red for the corresponding lane. While in H-AIM, IM rejects the request only if another vehicle with a green light is present at the intersection. H-AIM requires extra infrastructure to be integrated into the intersection management system to detect the presence of vehicles.

Semi-AIM [115] is a modified version of AIM that allows HVs and semi-autonomous vehicles to make reservations similar to CAVs. An interface e.g. a button is designed for HVs to send a request to the IM. In semi-AIM, three vehicle models were considered: i) semi-autonomous with communication (SA-COM) only, where the driver is permitted to pass if the entire lane is available, otherwise, it has to slow down and follows the traffic signal, ii) semi-autonomous with cruise control (SA-CC), where the driver gives the control to the driver agent to guide the vehicle through the intersection. Afterward, the control is given back to the driver. The vehicle will enter the intersection if it can maintain its velocity. Otherwise, it will act like the SA-COM model. iii) semi-autonomous vehicles with adaptive cruise control (SA-ACC) where the vehicle sends an anchor request to the IM and follows the front vehicle and enters the intersection if there is any. Otherwise, it will follow the SA-CC model.

In another effort to consider HVs, researchers have considered a connected vehicle center (CVC) [80] which can detect the movement and position of HVs through traffic detectors and set green periods for them to enter the intersection when they reach the edge of the intersection. By default, the light is red for all HVs and when the intersection is clear, CVC changes the light to green for HVs. A Fuzzy Rule-based System (FRBS) [98] was proposed for an intersection of CAVs and HVs where autonomous vehicles can detect the existence of HVs and take proper maneuver to avoid them. This approach does not use traffic light and is limited to scenarios where HVs enter the intersection from one road.

Fayazi *et al.* [47] proposed a device to be installed on the vehicle that suggests the desired speed (a range of speed) to the driver to follow so that it will reach the intersection at the desired time of arrival. This approach was tested on an actual vehicle and an API for the driver. In [111], Shen *et al.* propose to use an On-Board Unit (OBU) to convey different communication signals to HVs.



(a) Considering a safety buffer to account for localization errors and model mismatch

(b) Added safety buffer to account for round-trip delay.

Fig. 6. Different safety buffers considered to account for uncertainties

Two commands are envisioned for both CAVs and HVs, "pass" and "stop" and HVs are assumed to follow the command.

Supporting HVs at an automated intersection not only requires installing an extra device on vehicles, but it also needs training of drivers. Despite CAVs, HVs behavior may not be predictable and can disrupt the operation of the intersection. Therefore, the management approach should be flexible to handle HVs negligible mistakes or abnormal behaviors. Besides supporting human drivers, a management algorithm should account for pedestrians. So far, not much attention is paid to the management of pedestrians, and to the best of our knowledge, [97] is the only work that considers scheduling of pedestrians.

9 SAFETY AND ROBUSTNESS

Since intersection management is directly dealing with vehicles that transport humans, it should be safe and resilient against faults and uncertainties. Despite advances in localization approaches e.g. Simultaneous Localization and Mapping (SLAM) [17], localization of autonomous vehicles is not perfect yet.

Therefore, the IM should consider a larger size of the CAV when reserving a space-time slot for a vehicle to ensures that vehicles don't collide. We refer to this barrier as *Safety Buffer*. The size of the safety buffer is directly related to the accuracy and precision of sensors (encoder, IMU, GPS, camera, etc.) as well as the localization algorithms of the CAV and the maximum velocity of the vehicle. A common way to consider a safety buffer is depicted in Figure 6a (a). Figure 6a(b) depicts a safety buffer to account for position error due to round-trip delay. Besides position errors, there are a number of faults/anomalies that may occur during the operation of the intersection and can cause an accident. For example, a vehicle may break down inside the intersection or the intersection management software/hardware may crash.

Localization Errors: The AIM approach [41] considers a safety buffer around each vehicle to account for such uncertainties in the position due to inaccurate sensor readings (similar to Figure 6a). Belkhouche *et al.* [22] follow another approach and consider a safety margin between the cross-time of vehicles to account for uncertainties in the position of CAVs.

Network Failures: Network delay is an inherent part of the intersection management algorithm because CAVs communicate over a wireless network. In existing papers on intersection management of CAVs, it is assumed that CAVs trust the information that is received from other CAVs and schedule their cross-time accordingly. As a result, the safety of CAVs depends on the authenticity of the information and the timeliness of sending and receiving the information.

Processing time: In addition to network delay, checking the conflict between CAVs and determining a safe schedule –especially in optimization-based approaches takes time. Since CAVs are moving when waiting for a response from IM or other vehicles, the position at which they receive the response is dependent on the round-trip delay (RTD) i.e. from the moment they send a request and the moment they receive the response6b. Crossroads [8] proposes to do synchronization and timestamping to make sure CAVs and the IM have the same notion of time. Andert *et al.* propose to assign a "time to actuate" to each CAV to make vehicles behavior deterministic. By considering an upper bound on the RTD, on-time actuation of CAVs can be guaranteed.

Vehicle Model Mismatch Another source of error is the considered model for CAVs. Any inconsistency between the actual model and the considered model can result in accidents inside the intersection. Additionally, a vehicle may face external disturbances like wind, bump, etc. that can deviate its behavior from the expected one. There are many intersection management approaches where a reference velocity profile is assigned to the CAV (to track). Although such approaches work fine in ideal situations, they are not robust to an external disturbance (e.g. wind) or model mismatches (e.g. a small mismatch in a parameter) and they can affect the eventual arrival time of the CAV at the intersection. RIM [68] highlighted that the effect of bounded external disturbances and model mismatches can be compensated if a CAV tracks a reference position profile instead of a reference velocity profile.

Other Faults In the literature, researchers have modeled other sources of error and faults that can occur during the operation of the intersection. In a version of the AIM approach [40], authors assumed there is a way to let the IM know an accident has happened e.g. when the airbag sensor triggers and then stop other vehicles by informing them. Another fault model that is considered is a pedestrian/obstacle that suddenly starts crossing the intersection [76]. Li *et al.* proposed a method where the first CAV that detects the pedestrian, lets other CAVs know that there is an obstacle so that all CAVs stop. Dedinsky *et al.* [38] propose to use infrastructure-mounted cameras to improve the robustness of the intersection against faults. In a recent study, Khayatian *et al.* [66] proposed an intersection management approach called R2IM that is resilient against a "rogue vehicle", which is referred to a CAV that does not follow the IM's command (stops or accelerates) or share wrong information (deliberately or unintentionally). R2IM approach considers a large gap between the cross-time os CAVs to ensure the safety in the presence of a rogue CAV. It was proved that no accident will happen inside the intersection area as long as there is one rogue vehicle at a time. To avoid accidents, the intersection management approach should have certain detection methods. Not all scenarios can be detected from the exchanged data and therefore, there is a need for environmental sensors to doublecheck the status of the CAVs.

10 GRACEFUL DEGRADATION AND RECOVERY

In reality, unexpected situations can happen which temporarily disrupt the normal operation of the intersection e.g., an emergency vehicle approaching the intersection or a CAV breaking down inside the intersection. The intersection management approach should have certain mechanisms to resume the operation of the intersection once the emergency situation is resolved. We refer to the process of resuming the operation of the intersection as "recovery".

The AIM approach [40] has an inherent recovery mechanism integrated with it since it follows a QB-IM approach. When an emergency is detected, the IM rejects all requests until the emergency situation is cleared. Afterward, the IM starts accepting requests and will schedule CAVs.

Li *et al.* [76] propose a recovery approach for scenarios where a pedestrian suddenly attempts to cross the intersection. In this approach, another cooperative driving plan is regenerated when the road is cleared.

Resuming the operation of the intersection is crucial to the liveness of the system and in some scenarios, recovery may not be possible e.g. the intersection area is blocked due to an earthquake or falling tree. As a result, CAVs must have a built-in recovery algorithm to re-route.

11 SECURITY CONCERNS

Security is an important aspect of any intersection management since vehicles communicate over a shared medium (wireless communication). Security concerns are more serious in cooperative intersection management approaches since the vehicle that schedules the intersection can be malicious and cause a catastrophe.

Currently, modern vehicles have the potential of being the target of cyberattacks [30]. Such attacks can be done by physically accessing the vehicle e.g. connecting to the Controller Area Network (CAN) bus [71] or installing malicious applications [91]. Also, it can be done over wireless communication [30], e.g. using Bluetooth or cellular channel. Similar attacks can be applied to the intersection management system. Chen *et al.* [33] showed that a malicious agent can spoof the data that connected vehicles send to the Intelligent Traffic Signal System (I-SIG) and therefore, cause traffic congestion. In this attack, a malicious agent sends false data to deceive the I-SIG system and cause a traffic jam.

In [23], Bentjen *et al.* analyzed two attack scenarios: 1) Sybil Attack, where the Sybil attacker makes a false reservation or multiple reservations at a time. They showed that certain reservations that have the most number of conflicts with other paths will have the most significant effect on traffic congestion. 2) Squatting attack, where a CAV proposes to come to a complete stop within the intersection which forces the intersection manager to assign very low velocities to other CAVs and cause a traffic jam. The authors proposed to mitigate the Sybil by using a unique signed certificate for each message or installing environmental sensors to detect vehicles. They also proposed to mitigate the Squatting attack by specifying a lower-bound on the velocity of arrival that is proposed by CAVs.

Despite the fact that extensive research is done on cybersecurity of automobiles, not much research has been done on the cyber-security of intersection management systems. There can be different types of Sybil attack [39] that may be applied to the intersection management system: i) Nuisance, adding a delay in communication, ii) Herding, deceiving several intersection managers to control a variety of cars, iii) Carjacking where the attacker spoofs the assigned speed for one or multiple cars [23].

12 COMPARISON OF EVALUATION METHODS

In this section, we summarize the evaluation method of existing approaches. Some previous works use existing simulation tools, some developed their own simulation from scratch, some implemented an intersection with scale model vehicles, and some performed vehicle-in-the-loop (VIL) testing. Figure 7 shows an overview of some of the existing methods of evaluation. We categorized existing intersection management works based on their evaluation methods in Table 6.

SUMO[4] and VISSIM[6] are the most popular simulators that are used by the researchers. AutoSIM[1], Gazebo[2], and Synchro are other simulators that have been used by researchers. For a more realistic evaluation, researchers have developed scale model[8, 52, 68, 124]. There have been a few implementations that include full-size vehicle[47, 105] that are conducted using VIL.

Among existing simulators, SUMO is suitable for large-scale simulation and fast execution where the graphics are not important (simulates in 2D). SUMO, however, uses a simple model for

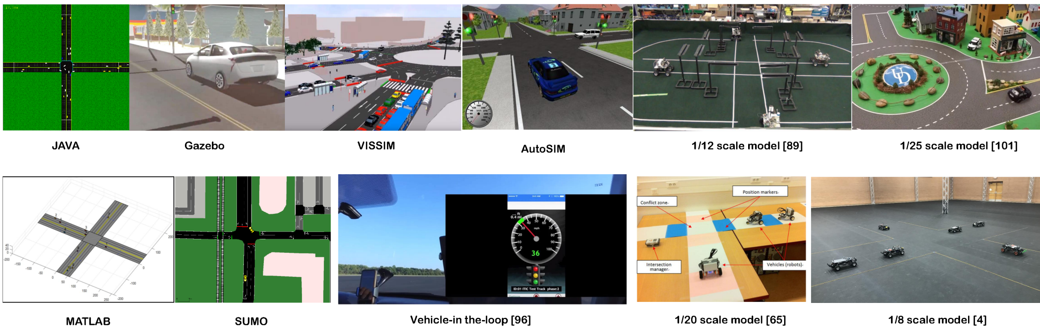


Fig. 7. Researchers have evaluated their algorithms using existing simulators, simulator that they have built from scratch, scale model intersections or vehicle-in-the-loop testing. Top row from left, 1) A simulator developed in Java for AIM approach [41], 2) Gazebo, 3) VISSIM, 4) AutoSIM, 5) A 1/12 scale model intersection by Fok *et al.* [52] 6) A 1/25 scale model intersection by Beaver *et al.* [20]. Bottom row from left, 1) A simulator developed in MATLAB [68], 2) SUMO, 3)Vehicle-in-the-loop testing by Fayazi *et al.* [47], 4) A 1/20 scale model intersection by Wu *et al.* [124], and 6) A 1/8 scale model intersection by Khayatian *et al.* [68].

Their Own Simulators	VISSIM [6]	SUMO [21]	Other Simulators	Scale Model Car	Vehicle in the loop
[10, 18, 23, 40–42, 44, 46, 54, 57, 58, 69, 75, 77, 84, 90, 98, 102, 109, 110, 115, 120, 127, 128, 130, 131, 133]	[33, 45, 73–75, 80, 92, 129, 130]	[49, 60–62, 86, 108]	[9, 15, 24, 48, 87, 114]	[8, 20, 52, 68, 99, 124]	[47, 105]

Table 6. Categorizing existing works based on their evaluation approach.

vehicle dynamics and therefore cannot model the behavior of vehicles accurately. Similarly, VISSIM can perform large-scale simulations but it provides a 3D view and it can integrate high fidelity models (e.g. from CarMaker). VISSIM is relatively slower than SUMO. Both SUMO and VISSIM can model pedestrians too. Gazebo simulator has a good physics engine and graphical representation. Gazebo can simulate multiple vehicles in 3D and accurately simulate vehicle sensors including LIDAR, Camera, RADAR, Ultrasonic, etc. Gazebo, however, compute-intensive and requires a high-performance computer to run smoothly when modeling multiple vehicles. Synchro and AutoSIM are other simulators that are not well documented and rarely used. The integration of an intersection management algorithm with Synchro and AutoSIM is challenging.

Currently, the state-of-the-art approach for intersection management of vehicles (either AVs, CAVs or human-driven vehicles) is through controlling the traffic light and signal free approaches have not been deployed yet to the best of our knowledge. Signal-free approaches are expected to be tested on private test tracks like M-City [27], GoMentum Station[37], or Taiwan Car Lab[119] first before the actual deployment on public roads.

Simulation-based evaluations are simpler to implement and reproduce, and easier to scale. However, a simulation may not capture all challenges of an actual deployment. For instance, the effect of network delay, vehicle model mismatch, computation time on the operation of the system, and the need for implementing clock synchronization, fail-safe routines, etc. are some challenges of a real implementation.

13 CONCLUSION AND FUTURE WORKS

In this article, we conducted a survey on existing approaches for managing intersections of CAVs. We enumerated key aspects of developing a real-life intersection management method and studied existing works with respect to these aspects. Although extensive studies have been done on intersection management of CAVs, actual deployment of them is far from happening. This is mainly because most existing works are focused on improving the throughput of the intersection and very little research is done on security, robustness, and reliability of the intersection management. We conclude with most important takeaways and challenges that are left open for researchers to tackle:

V2V/V2I Interface Depending on the interface used for the management of CAVs, the network overhead varies. For instance, V2V approaches have higher overhead compared to V2I ones due to the topology of the network, and query-based approaches (QB-IM) have higher overhead compared to assigned-based techniques (AB-IM) due to the nature of the intersection management interface. Additionally, network overhead changes based on the total size of the data that should be exchanged among CAVs. In terms of scalability, V2V approaches are more popular as they do not require support from the infrastructure and more reliable as the IM can be the single point of failure. Although many intersection management algorithms are proposed for CAVs, there are other things that should be considered in the design phase, which affects the final deployment e.g. the number of lanes, lane width, allowing u-turn, allowing turns from specific lanes, etc. As a result, an ideal intersection management algorithm should be flexible to be applied to different intersection types.

Vehicle Scheduling Policy There is a trade-off between fairness and the wait time of CAVs and they both should be taken into account when the scheduling policy is developed. To figure out how much deviation from fair scheduling is acceptable by the public, research in other fields like psychological needs to be conducted. Another important metric for a scheduling policy is computation overhead, which has not received much attention. It is desired to have a small processing time in order to keep the safety buffers around vehicles to be small, which of course leads to more efficient management. Also, there is a relationship between the computation time of the scheduling algorithm and the size of the intersection. If the processing time is large, then CAVs have to start communicating farther back in order to receive a reservation in time. Worst-case Execution Time (WCET) analysis is required to set an upper bound on the processing time of the scheduling. Optimization-based scheduling techniques achieve better throughputs compared to other methods but their processing time to find the optimal solution is larger. Finding balanced scheduling policies that are computationally light-weight, have bounded wait time in terms of fairness and are efficient remains an open problem to be solved.

Wireless Technology In order to operate the intersection, the network delay should be small enough. The network delay depends on many factors but importantly the total number of CAVs that intend to communicate and the number of packets transmitted per CAV. Therefore, these factors should be taken into account when the intersection management algorithm is designed to verify their scalability.

Vehicle Dynamics Model Fidelity of the considered model for the vehicles corresponds to the accuracy of predicting their behavior. Although complex models are more accurate, they require more computational resources and it may not be practical to use in real-time when the number of vehicles increases. Also, there is a relationship between the inaccuracy in the model and the size of the safety buffer considered for each CAV. Finally, it is also worth noting that developing an intersection management algorithm based on a fixed model can result in a brittle system that can fail. As a result, a robust design should be adaptive where the parameters of the model are determined at the runtime.

Multiple Intersections Management Management of multiple intersections can be very compute-intensive for fine-grain models (when individual vehicles are considered). On the other hand, managing vehicles based on a coarse-grain model (when abstract information is used e.g. flow of traffic) is computationally less expensive but will be more inaccurate. Finding the right granularity for processing the information and management depends on the allotted computational resources.

Support for Human-driven Vehicles (HVs) A realistic intersection management interface should be compatible with HVs since there will be a period where humans share the road with AVs. Therefore, either traffic lights remain in charge of managing the intersection or on-board devices should be used. In addition, intersection management should account for the crossing of pedestrians. Pedestrians can use a device to (push buttons at the crosswalks, or cell phone) get a reservation from the intersection.

Safety and Robustness Ideally, a proof for safety must be presented for an intersection management approach and its robustness should be evaluated with respect to different fault models. Besides uncertainties in the position due to sensor error and model mismatch, there are other fault models (e.g a car becomes does not follow IM's command) that can cause an accident. A thorough study must be done to identify such faults and proper safety measures should be envisioned in the design.

Graceful degradation and Recovery In case of an emergency, the intersection operation stops. Therefore, recovery should be a part of the intersection management algorithm too. Liveness analysis should be done for an intersection management algorithm to ensure it's deadlock-free.

Security Concerns Security countermeasures should be implemented at different levels to keep the intersection management system safe. Despite its importance, a very little study is done on the security of intersection management algorithms. As a prerequisite, an intersection management method should be tested when typical attacks are performed.

Evaluation methods Although simulation helps to evaluate the efficiency of an intersection management algorithm, in most existing simulation-based evaluations, practical issues are neglected that can affect not only the safety but efficiency of the algorithm. Also, in existing real implementations, either a single vehicle is used (vehicle-in-the-loop) or scale model vehicles with low velocity are used.

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