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Review

Urban traffic signal control with connected and automated vehicles: A survey

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ABSTRACT

Inefficient traffic control is pervasive in modern urban areas, which would exaggerate traffic congestion as well as deteriorate mobility, fuel economy and safety. In this paper, we systematically review the potential solutions that take advantage of connected and automated vehicles (CAVs) to improve the control performances of urban signalized intersections. We review the methods and models to estimate traffic flow states and optimize traffic signal timing plans based on CAVs. We summarize six types of CAV-based traffic control methods and propose a conceptual mathematical framework that can be specified to each of six three types of methods by selecting different state variables, control inputs, and environment inputs. The benefits and drawbacks of various CAV-based control methods are explained, and future research directions are discussed. We hope that this review could provide readers with a helpful roadmap for future research on CAV-based urban traffic control and draw their attention to the most challenging problems in this important and promising field.

1. Introduction

Urbanization has incented dramatic growth of car usage in more and more cities globally. Motor vehicle miles have increased by 167% in the United States from 1970 to 2009 (U.S. Census Bureau, 2012). As a result, growing traffic congestion, accidents, and pollutions are threating sustainable mobility for our future. Various traffic management methods have been proposed to handle the fast-growing travel demands. For example, many cities are building better public transportation systems and launching low-price tickets to reduce private car usage (Ding et al., 2018; Nuzzolo and Comi, 2016). Ride-sharing is also advocated by many local governments to reduce car ownership (Dong et al., 2018; Nie, 2017).

Urban traffic control (UTC) systems have also been continuously updated and innovated to keep up with the increasing traffic demands (Wang, 2010; Hamilton et al., 2013; Li and Wang, 2018). Among many new techniques developed for traffic control recently, connected and automated vehicles (CAVs) are believed to have great promises (Mahmassani, 2016). Usually, connected vehicles (CVs) refer to vehicles that can communicate with other vehicles (vehicle-to-vehicle, V2V), infrastructure (vehicle-to-infrastructure, V2I), and other traffic participants such as pedestrians and bicyclists (V2X). Fully automated vehicles refer to "*the vehicle can do all the driving in all circumstances. The human occupants are just passengers and need never be involved in driving*" (NHTSA, 2016). The U.S. Department of Transportation's National Highway Traffic Safety Administration (NHTSA) defined five levels of automated driving, from driving assistance (Level 1) to fully automated vehicles (Level 5). The automated vehicles discussed in this paper belong to Level 5.

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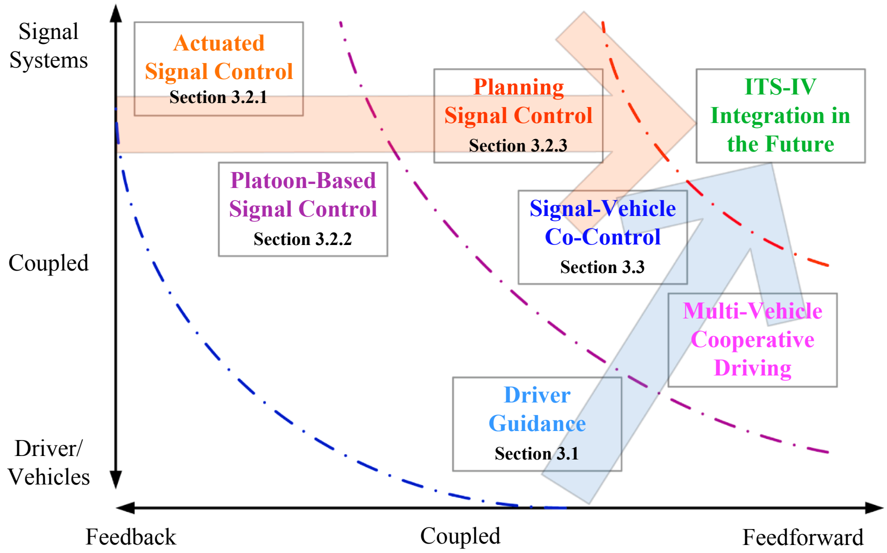

Fig. 1. An illustration of different topics on urban street traffic control with CAVs.

The benefits of introducing CAVs include but not limited to crash reduction/elimination, travel time reduction, energy efficiency improvement, and others. Focusing on urban traffic control, we may reach the following goals with the aid of CAVs techniques:

- CAV data can be used to better estimate the performance of traffic flow states and traffic control for signal timing;
- Traffic control systems could make better signal timing plans, since the arrivals of vehicles could be better predicted in advance;
- Drivers or fully automated vehicles could better adapt their operations to cooperate with signal timing to reduce overall congestion and fuel consumption in urban areas.

To further discuss the state-of-the-art findings obtained for CAV-based urban traffic control, we need to first clarify the topics that will be covered in this paper. Usually, the technologies for advanced traffic control systems, advanced driver assistance systems (ADAS), automated vehicles, and connected vehicles often overlap with each other. Existing studies in this field may focus on related but distinguished topics. Some studies only considered the traffic signal systems, while other studies took both signal systems and vehicles into considerations. From the viewpoint of control schemes used in these studies, some only applied feedback control, while others mainly relied on feedforward trajectory planning.

Fig. 1 depicts the underlying evolution of the design philosophy and research paradigms for UTC. The upper arrow represents the trend of considering more vehicle driving management in traffic control systems, while the lower arrow represents the trend of considering more traffic flow management in vehicle control systems. The curves divide three stages of transportation-vehicle integration (from lower left to upper right): the past, the current, and the future. As shown in the figure, we can roughly categorize existing studies for CAV-based traffic control into six types of approaches, namely, *driver guidance*, *actuated (adaptive) signal control*, *platoon-based signal control*, *planning-based signal control*, *signal-vehicle coupled control (SVCC)*, and *multi-vehicle cooperative driving without traffic signals*.

The introduction of CAV in UTC had linked two research fields: ITS (i.e., transportation) and IV (i.e., vehicles) which were studied mostly separately during the last 30 years. Although the initial attempts focused on either the vehicle or the traffic control system, we are now composing the vehicle part and the traffic control systems into a more and more tight integration.

This integration brings New Hope, New Changes, and also New Problems!

- The objective has been extended from traffic efficiency to safety, energy economics, and pollution reduction.
- The decision variables have become the motion planning and control of each individual vehicles, in addition to the phases, cycle length, green ration, and coordination of traffic signals.
- The descriptions/models of the traffic systems have been gradually replaced from the continuous traffic wave model to the movements of each individual vehicles.
- The solution strategies have been shifted from traffic-responsive feedback control to planning based feedforward control.
- The solving methods have been changed also. For example, artificial intelligence (AI) techniques have been widely used now.

To provide an overview of the technologies, benefits, and challenges of these changes, we sequentially review the first five types of approaches. The sixth type of approaches on multi-vehicle cooperative driving will not be covered in this paper for reasons explained below.

Although several literature reviews on traffic control (Florin and Olariu, 2015; Li et al., 2014c; Olia et al., 2016) have been made in this field, our surveys provide the following new insights:

First, we highlight the use of CAVs in traffic flow sensing and estimating, since the absence of reliable traffic state measurements has been shown to be one of the main obstacles that hinder the successful applications of appropriate traffic control. Many recently proposed traffic control methods have verified the importance and merits of CAV-based traffic sensing (Sharifi et al., 2017). In this paper, we would like to provide a timely survey on this topic.

Second, we focus on the traffic control problem with mixed CAVs and human-driven vehicles. In other words, we emphasize the role of the traffic signal control system to guide the movements of vehicles, while at the same time allow the CAVs to change their movements to cooperate with the signal systems adaptively. We believe that the traffic signal control system will remain critical at least in the near term when mixed human-driven vehicles or non-connected vehicles and CAVs co-exist in the traffic system. Hence, we do not review the sixth approach, i.e., multi-vehicle cooperative driving without traffic signals, in this paper. Readers who are interested in cooperative driving around non-signalized intersections may refer to some other surveys and papers (Chen and Englund, 2016; Lee and Park, 2012; Li et al., 2014c; Meng et al., 2018; Qian et al., 2017; VanMiddlesworth et al., 2008; Xu et al., 2018) for detailed discussions.

Third, we review/address some practical yet essential topics related to CAV-based traffic control, including the transit priority control, network control, impacts of CAVs penetration, safety guarantee for CAV-based traffic control, and the implementation requirements of CAVs technologies. To the best our knowledge, such topics have not been well discussed in the literature in a systematic manner.

We arrange the rest of this paper as follows. Section 2 summarizes how to collect and retrieve traffic information by CVs (or similar technologies such as mobile sensing) with increasingly available data and improved measurement accuracy. This summary provides a basis for the later survey. Section 3 summaries the advanced control technologies used to improve traffic performance. The driver guidance system is first discussed in Section 3.1; followed by signal control methods (Section 3.2) including actuated signal control, platoon-based control, planning-based control, and transit priority control; Section 3.3 discusses the newly emerged signal-vehicle coupled control. Section 4 provides some discussions and future research directions for CAV-based traffic state estimation and signal control. Section 5 concludes the paper.

2. Traffic information collection and state estimation by CAVs data

2.1. The evolution of traffic information collection techniques

Fixed sensors (e.g., loop detectors and video cameras) became pervasive in cities since the end of the last century and helped collect valuable traffic information to support the development of the first-generation intelligent transportation systems (Kurzhanskiy and Varaiya, 2015). However, fixed sensors can only provide the information of traffic flow measured at discrete spatial points (Sun and Ban, 2013), and we need to build special models to estimate the traffic states at other spatial locations. Because not any traffic flow model or estimation method is perfect, we always expect to fuse additional traffic information to increase estimation accuracy (Berkow et al., 2009; Bhaskar et al., 2011, 2014).

Most early attempts in this direction studied probe vehicle based traffic monitoring systems using wireless location technology (Ou et al., 2011; Smith et al., 2004). These approaches sampled a portion of vehicles as they traversed the network. Either wireless location technology or Global Position System (GPS) were used to record the specific locations (i.e., latitude/longitude) of these probe vehicles sampled along with their trips. Then, specific measurements of traffic flow (i.e., queue length and travel time) were estimated based on the sampled data (Ban et al., 2011; Cheng et al., 2012). Compared with fixed sensors, these approaches were able to provide more information of the traffic flow, which could improve our knowledge on traffic states and detect errors of fixed sensors (Li et al., 2014b).

Conventional probe vehicle based data have limited scope and time. Since the last decade, the CVs techniques have achieved significant advances, making it possible to access a great deal of more accurate, and multi-dimension information of traffic flow in real time (Massaro et al., 2017). The newly available high-resolution trajectory data of individual vehicles could increase our understanding of traffic flow states, which are critical to traffic control. In fact, the V2I based CVs data collection techniques have not been widely implemented. Some other technologies, especially the mobile sensing technique (Hoh et al., 2008; Sun and Ban, 2013), could also provide high precision trajectory data, which is similar to the location data that CVs could provide. Therefore, we include the studies based on both mobile sensing and CVs data in this section.

We emphasize the difference between conventional probe vehicle based data and the CVs data (or mobile sensing data) by two aspects. First, the resolution levels of trajectories and the penetration-rates of sampling vehicles for probe vehicle based approaches are much lower than those for CVs based approaches. As a result, we usually need to divide the roads into grids and use the data collected by probe vehicles to estimate the average traffic flow states (e.g. average speed, average density) within each grid (He et al., 2017; Jiang et al., 2017a; Ran et al., 2016). In contrast, with the high-resolution data collected by CVs, we can characterize the trajectories of each sampled vehicles and may also derive the trajectories of other neighboring vehicles that are not sampled (Wan et al., 2016; Xie et al., 2018).

Second, constrained by the resolution level and the amount of data, most probe vehicle based approaches are not suitable for real-time traffic control. Instead, such data were usually used to estimate freeway traffic flow states or vehicle travel times (Montanino and Punzo, 2015; Seo and Kusakabe, 2015; Van Lint, 2010). In contrast, real time data collected by CVs and mobile sensing can be used to real-time traffic control.

As shown in Fig. 2 and inspired by Sun and Ban (2013) and Zheng and Liu (2017), there are basically four types of information

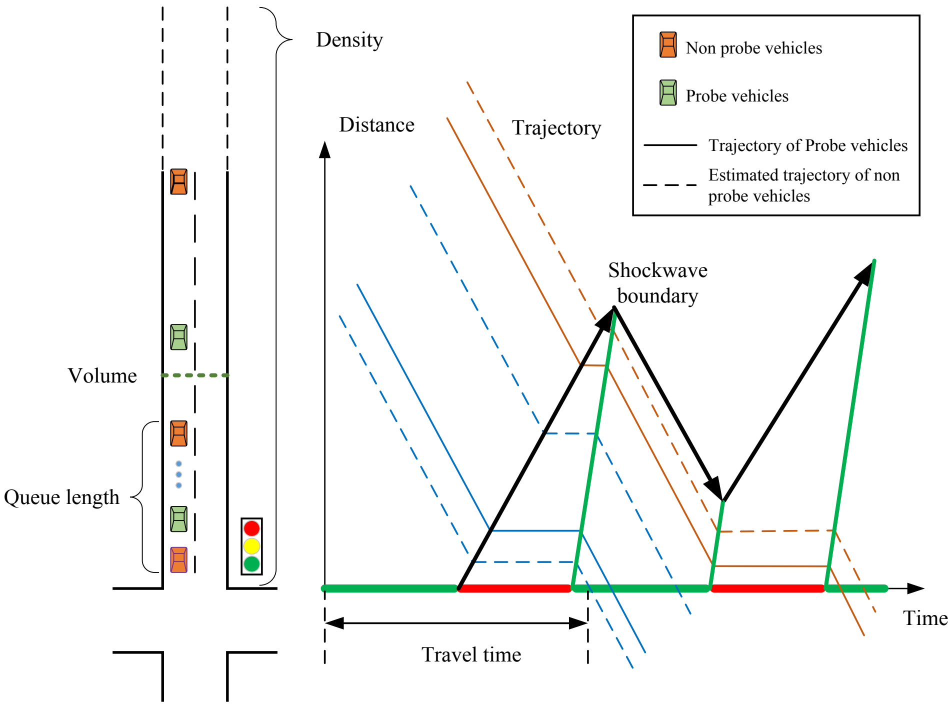

Fig. 2. An illustration of traffic information estimated based on V2X (or mobile sensing) data.

which could be used to measure the performances of traffic signal control: flow volume, travel time, queue length, and shockwave boundary. Flow volume can be obtained by fixed sensors or estimated using CVs data. The rest three types can be accurately measured only if CVs are used.

Conventionally, we often use two performance indices for traffic efficiency: point delay (that caused by traffic control devices such as traffic signals and STOP signs) and queueing length (HCM, 2010). With the information feedback from CVs, we can accurately estimate not only the point delay of each vehicle but also the spatial evolution of the queues in real time (Ban et al., 2011). Many recent studies showed that segment delay (that combines the point delay and other delays incurred within the segment) could be a more appropriate performance index (Day et al., 2017; Gan et al., 2017; Hunter et al., 2012; Li et al., 2015; Wang et al., 2016). In addition, CVs make it possible to obtain the accurate real-time estimation of the time-varying queue length and boundaries of shockwaves. Several different algorithms have also been proposed to accurately estimate travel time of vehicles, especially when only a limited number of vehicles are connected (Araghi et al., 2016; Ernst et al., 2014; Haghani et al., 2010; Sharifi et al., 2017; Zheng and Van Zuylen, 2013).

Since appropriate traffic estimation is indispensable for traffic control. In this paper, we only review the studies related to the performance measurement of urban traffic that is crucial for traffic signal control using CAV or mobile sensing data. Table 1 (attached at the end of this paper) summarizes the existing studies in the literature, where most of the reviewed papers were published within the last decade. We can also find that most of the studies required trajectory data as the input, while a few of them used reduced data (such as vehicles travel times) when considering privacy protection. Queue length was the most popular performance measure, and other measures included travel time (or delay), volume, density, trajectory, and shockwave boundary. In addition, most methods focused on real-time traffic state estimation. Many studies focused on a single intersection in under-saturated traffic, while a number of them could deal with multiple intersections in over-saturated traffic. The outputs of these methods could be deterministic or probabilistic estimations. Based on the specific approaches in each study, we can roughly divide the existing methods into two categories: *deterministic* and *stochastic* approaches. In the following two subsections, we will discuss them respectively.

2.2. Deterministic approaches

The deterministic approaches can be further divided into two kind of approaches: *shockwave-based* and *kinematic equation-based approaches*. The shockwave-based approaches usually assume that vehicle trajectories could be considered as piecewise linear curves and then try to locate the critical patterns or points of these curves (e.g., boundaries of shockwave) to derive traffic flow measures. The kinematic equation-based approaches apply kinematic equations to describe the dynamics of individual vehicles and then derive traffic flow states. Such approaches often consider the acceleration and deceleration of vehicles, which may help derive more accurate traffic flow measures.

Most shockwave-based approaches make additional assumptions on vehicle arrival patterns (e.g., uniform arrivals and Poisson arrivals) and transfer the traffic measurement estimation problems to certain optimization problems. The objectives of these

Table 1
Traffic information extraction via V2X paper summary.

	Papers	Input data		Performance measures						Real time or not		Output		Under/Over-saturated		Intersection types	
		Traj.	Redu.	Q.L.	T.T.	Den.	Vol.	Traj.	S.B.	Yes	No	Deter.	Distr.	Under	Over	Single	Multi
Stochastic Learning	Comert and Cetin (2009)	√		√							√	√		√		√	
	Comert and Cetin (2011)	√		√						√			√	√		√	
	Hao et al. (2014)		√	√						√			√	√	√	√	
	Comert (2013)	√		√						√			√	√		√	
	Hao et al. (2013)		√	√						√			√	√	√	√	
	Marinica et al. (2013)	√		√						√			√	√	√	√	√
	Hofleitner et al. (2012)	√		√	√					√			√	√	√	√	√
	Zheng and Liu (2017)	√					√				√			√			√
	Rompis et al. (2018)	√		√				√		√			√	√		√	
	Ramezani and Geroliminis (2012)	√			√					√			√		√		√
Shockwave-Based	Ramezani and Geroliminis (2013)	√		√					√		√	√		√	√	√	√
	Ramezani and Geroliminis (2015)	√		√					√		√	√		√	√	√	√
	Han et al. (2014)	√		√						√		√		√	√	√	√
	Ban et al. (2009)		√		√					√		√		√	√	√	
	Sun and Ban (2013)		√	√						√		√		√		√	
	Cheng et al. (2012)	√		√	√	√				√		√		√		√	√
	Hiribarren and Herrera (2014)	√		√		√				√		√		√	√	√	√
	Cai et al. (2014)	√		√				√		√		√		√	√	√	√
	Hao and Ban (2015)		√							√		√		√	√	√	√
	Ban and Gruteser (2010)		√	√	√		√			√		√		√		√	√
	Hao et al. (2012)		√	√						√				√	√	√	
	Ban et al. (2011)		√	√	√			√		√		√		√	√	√	√
Kinematic Equation-Based	Hao et al. (2015)		√	√	√			√		√		√		√	√	√	√
	Liu and Ma (2009)	√		√					√	√		√		√		√	√

Note: Traj. – Trajectory; Redu. – Reduced; Q.L. – Queue length; T.T. – Travel time; Den. – Density; Vol. – Volume; S.B. – Shockwave boundary; Deter. – Deterministic; Distr. – Distributions.

optimization problems are usually to minimize the errors of estimated traffic measures (e.g., vehicle trajectories, travel time) with the observed measures. The empirical observations and the assumed traffic flow models are also considered as constraints in these optimization problems.

Ban et al. (2009) proposed a two-step least square based shockwave-based approach to estimate the delay (travel time) patterns of signalized intersections. They assumed that the arrival pattern was uniform and the sample travel times of vehicles passing through an intersection were known from mobile sensors. They approximated the delays by piecewise linear curves based on the queue forming/discharging process and identified the signal cycles by detecting the delay changes. Within each cycle, the least square based linear fitting algorithm was used to estimate the delay pattern. Tested by both experimental and simulation data, the proposed method could be 10% more effective than a benchmark linear interpolation approach under varying penetration rates. Ban et al. (2009) were among the first to recognize the potential of mobile sensing data for estimation the performances of signalized intersections when such data reach meaningful penetration (e.g., 5–10% or more). Furthermore, instead of using traffic volume or density that was the primary input to fixed-location-sensor based traffic estimation methods, only mobile data (such as sample vehicle travel times) were used in the estimation method in Ban et al. (2009), which represents a class of "mobile-sensing-data-based" traffic modeling methods. Such methods are featured by integration of traffic principles (such as traffic flow theories) and data analytics approaches (optimization or statistical learning approaches) (Hao et al., 2012; Hofleitner et al., 2012).

Ban et al. (2011) presented another shockwave-based method to estimate the real-time queue length at signalized intersections using only sample travel times. The key idea of their method was also that the critical pattern changes of travel times were associated with the signal timing and queue length changes. The authors first assumed uniform arrivals with different rates in different cycles and the signal timing is known. The concept of Queue Rear No-delay Arrival Time (QRNAT) was then introduced. Based on the queue forming and discharging processes, the queuing delays could be estimated by detecting the discontinuity patterns of sample travel times. Queuing delays were used to estimate QRNATs, which were then used to estimate the maximum and minimum queue lengths of a cycle. Both field experiments and simulations showed promising results when the penetration rate is relatively large (e.g., more than 30%). Ramezani and Geroliminis (2015) presented an integrated method to estimate queue shockwave profiles at signalized intersections in urban networks. By assuming that the arrival distribution, the position, and the velocity of the sampled vehicles were known, they first classified the data into moving and stopped classes by a threshold-based classifier. Then, the stopped data were identified into different cycles based on a projection profile clustering algorithm, and the moving data were assigned to corresponding cycles by a linear boundary. Based on the Lighthill-Whitham-Richards (LWR) traffic flow model, they formulated the estimation of the queue front for each cycle as a constrained least squares problem. The back of the queue was identified by a piecewise linear function, whose number and attributes were determined by a curve-fitting nonlinear optimization method. This methodology was proved to be promising and robust according to the numerical results using both NGSIM field data and simulation data.

Apart from using the critical pattern changes of travel times, detecting the critical points of shockwaves also received increasing attention. Cheng et al. (2012) proposed a shockwave-based method to estimate the cycle by cycle queue length at signalized intersections based on vehicle trajectory data. They first modeled the trajectories based on the LWR theory. Then, a threshold-based critical point algorithm was developed to extract the critical points, which represented the changes in vehicle dynamics. The critical points were filtered for different purposes, i.e., queue estimation and signal timing estimation. They were then used to detect the signal timing plan that provided the basis for queue length estimation. The method was tested in both simulation and NGSIM data. The results showed that the mean absolute percentage errors of maximum queue length estimation under different scenarios were around 20%.

The shockwave-based methods have solid theoretical foundations and are efficient considering the computational effort. However, there are two drawbacks of this type of methods. First, the computation burden would be heavy if the physical models or optimization techniques are complex. To overcome this problem and make it feasible for real-time traffic control, many recent studies formulated the optimization-based models into relatively simpler problems such as least square optimization (Ban et al., 2009; Ramezani and Geroliminis, 2015), quadratic optimization problem with linear constraints (Hao et al., 2012), or dynamic programming (Sun and Ban, 2013), which could be solved easily by existing solvers. Second, the accuracy of the shockwave-based methods is relatively lower compared to the other methods. This is because detecting critical patterns and points will introduce errors, especially when real-world data are used. Furthermore, the shockwave-based methods often ignore vehicles' accelerations and decelerations, which may also influence the estimation performance. The kinematic equation-based method could help resolve this problem by focusing on the dynamic movement of an individual vehicle.

Hao et al. (2015) presented a kinematic equation-based method to estimate the location of a vehicle in the queue based on the vehicle's travel time traversing a signalized intersection. They assumed that the acceleration and deceleration rates are constant for one vehicle but could vary for different vehicles. Specific kinematic-based equations were developed for different cases of through vehicles and left-turning vehicles, with considerations of possible over-saturations. By focusing on the queue discharging process, the kinematic equations can help estimate the location of a sample vehicle in the queue and when it joined the queue. The method was tested using data from simulations, a field test, and NGSIM. The results showed a higher success rate compared to the optimization-based methods in Ban et al. (2011). One of the main reason for the improved performance is that the method in Hao et al. (2015) did not assume uniform arrivals.

2.3. Stochastic approaches

The above deterministic methods simplify the real traffic as deterministic processes, which may introduce certain estimation errors. In contrast, some stochastic methods (i.e., stochastic learning-based methods) were then developed to address these issues.

Stochastic approaches usually assume certain arrival distributions (e.g., uniform distribution, Poisson distribution), and builds specific stochastic models to describe the evolution process of the studied traffic flow variables for different traffic scenarios. The estimated performance measures (e.g., queue length, travel time) can then be derived as the expected values of the modeled random variables. Compared to deterministic methods, the main advantage of stochastic methods is that they can cope with incomplete/erroneous/sparse empirical data and oversimplified traffic flow models. This feature makes them more desirable in practical applications. Furthermore, to attain better performances, deterministic methods usually require relatively higher penetration of the available data, which may not be practical in many real-world applications.

Such approaches could be divided into model-based methods and data-driven methods. So far, most stochastic filtering and particle filter techniques are model-based and try to integrate traffic flow models with data; while the pure data-driven methods such as deep-learning based methods depend solely on data (Lv et al., 2015; Ma et al., 2015, 2017; Polson and Sokolov, 2017).

Comert and Cetin (2009) proposed a sampling based model-based approach to estimate the average queue length at signalized intersections and its variance by using sample vehicles' trajectory data. Comert (2013) further developed analytical models for the real-time estimation of queue lengths and analyzed the estimation errors under different penetration rates as well as volume-to-capacity ratio levels. They assumed the arrivals follow Poisson distribution with a known arrival rate. In addition, the sample vehicle penetration rate and signal phase durations were also assumed to be known. Based on these primary parameters, they derived the probability distribution of queue locations and queue joining times of sample vehicles. For the cases without overflow queues, they generated fully analytical closed-form expressions for mean and variance of the queue length estimators. For overflow cases, approximation models were derived. Compared with the results from VISSIM microscopic simulations, the presented models could limit the estimation error within ± 4% at all volume-to-capacity ratios and sampled penetration rates.

Comert's probability analytical methods require queue locations and queue joining times as the input, which may not be available directly from CVs or other mobile data sources. Hao et al. (2014) presented a Bayesian network based method for the real-time queue length distribution estimation at signalized intersections, which only needs the travel times of sample vehicles as the input. They first defined the virtual trip lines (VTL; see Hoh et al. (2008) and Sun et al. (2013)) at an upstream location and a downstream location of the intersection, from which the sample travel times could be collected. Then they classified traffic conditions and sample scenarios into seven cases based on the sample travel times. For each case, a Bayesian network model was built by modifying a pre-defined three-layer Bayesian network in Hao et al. (2013) for vehicle index estimation. After computing the conditional probability of hidden variables using given sample travel times and vehicle indices, they finally calculated the queue length distributions for each case. Tested by both field experiments and simulation data, the proposed method was proven to be more accurate and robust compared to the linear fitting method and queue location method developed previously.

In addition to queue length, traffic volume is another important measurement to signal control. Zheng and Liu (2017) proposed a maximum likelihood method to estimate traffic volume using the trajectory data of CVs. Modeling vehicle arrivals as time-dependent Poisson process (also used in Hao et al. (2013)) and observing trajectories from CVs approaching to the intersection, they formulated the volume estimation problem as a maximum likelihood problem and solved it by an expectation maximization (EM) procedure. Tested under real-world data, the proposed method could limit the estimation errors within 9–12% for intervals of 30 min and 1 h, even under a low CV penetration rate (10%).

Other stochastic filtering techniques such as Kalman filter (Guo et al., 2014; Tampère and Immers, 2007), particle filter (Gustafsson et al., 2002; Marinica et al., 2013), and other machine learning based approaches (Lv et al., 2015; Rompis et al., 2018) have been applied to help estimate queue lengths, travel times, and volumes under disturbances.

As the quantity of available data and the computation speed receive increased attention, data-driven machine learning based methods have been receiving increasing attention recently. These methods could be regarded as a special type of stochastic approaches, since almost all the data-driven machine learning methods would use the maximum likelihood or Bayesian approach to estimate the hidden variables and thus minimize/maximize the expectations.

There are however some differences between the newly emerged data-driven machine learning methods and conventional stochastic methods. First, the former focuses more on prediction accuracy even at the expense of interpretability, while the latter cares more about the statistical inference and interpretability of the model and results. Second, data-driven machine learning methods do not rely on explicit models but usually require much more data than conventional methods. Third, the former might outperform the latter given a special case with sufficient data. However, the computation burden of the former may be high; while the fault tolerance and transferability would be lower than those of the latter. There are certainly tradeoffs between these two types of stochastic approaches, which should be carefully evaluated and selected when specific applications are concerned.

For example, Lv et al. (2015) proposed a deep-learning based algorithm to predict the traffic flow. They used the stacked autoencoder to learn the latent traffic flow features, which could discover the nonlinear spatial and temporal correlations from the traffic data. The greedy layerwise unsupervised learning algorithm was used to train the deep network. After fine-tuning and parameters iteration, the algorithm was tested on the Caltrans Performance Measurement System (PeMS) database. The results showed that this deep-learning based method could outperform other competing algorithms like support vector machine (SVM) and radial basis function neural network model.

2.4. Summary

Deterministic approaches differ from stochastic approaches in the following aspects. First, deterministic approaches can only generate deterministic outputs, while stochastic approaches may produce distributions of traffic flow measures that contain richer information. Second, stochastic approaches are more robust and less sensitive to data errors and usually perform better under lower penetrations of CVs. Third, stochastic approaches usually require more computation times, while deterministic approaches are simpler and more efficient in computation. Researchers may choose either type of approaches according to specific applications and other practical requirements.

According to what we have surveyed, we summarize several practical considerations of the CAVs (or mobile sensing) based traffic state estimation techniques for traffic signal control. First, traffic states of over-saturated traffic and multiple intersections (even networks) should be further studied. The over-saturated traffic condition is an important part of the real traffic, while defining and estimating the network traffic performance is crucial for network-wide signal optimization and coordination. Second, the tradeoff between accuracy and efficiency should be well considered when designing the traffic state estimation algorithms, especially when stochastic learning methods are applied. Third, apart from the conventional measures discussed above, the estimation and prediction of vehicles trajectories are receiving more attention due to the great potential of improving the traffic signal control algorithms based on trajectories (Cai et al., 2014; Rompis et al., 2018). Research in this direction is expected to gain more momentum in the near future, especially when associated issues such as privacy protection can be properly addressed.

Last but not least, most of the studies used vehicle trajectory data directly, which however may violate the privacy of individual vehicles/users (Hoh et al., 2008, 2012; Sun et al., 2013). Privacy is an important aspect of cybersecurity when emerging technologies are concerned in transportation, which is closely related to the collection and use of the data from such technologies (e.g., CAVs and mobile sensing) for traffic state estimation and related purposes. Privacy research in transportation and in particular for urban traffic control is still in its early stage; many transportation researchers still view privacy protection as a limiting factor for them to acquire/access data. In this new era of technologies and big data, however, privacy needs to be considered and addressed seriously for at least two reasons. One is that if we do not, future regulations may be in place to restrict what types of data we could collect and use from these technologies. The recent Facebook scandal (Rosenberg et al., 2018) has clearly shown this. More importantly, considering privacy in transportation modeling can indeed provide new opportunities to design smarter data collection and modeling schemes by collecting only the most relevant data (and thus not only to protect privacy but also to reduce data storage and transmission) and developing innovative modeling techniques to utilize the collected data to satisfy the data needs of various application. Recently developed concepts of virtual trip lines (VTL; see Hoh et al. (2008)) and VTL-zones (Sun et al., 2013), and methods such as privacy by design to "co-design" privacy techniques and modeling methods (Cavoukian, 2009; Ban and Gruteser, 2010), are some examples on how privacy may be simultaneously considered when modeling methods are developed. We expect privacy research will receive more attention in the near future especially for urban traffic control applications.

3. Advanced traffic control under CAVs

CAV-based traffic control can be broadly categorized as single intersection control, multi-intersection coordinated control of a traffic corridor, and network traffic control; see Fig. 3. In this paper, we first discuss single intersection control since it is the basic unit

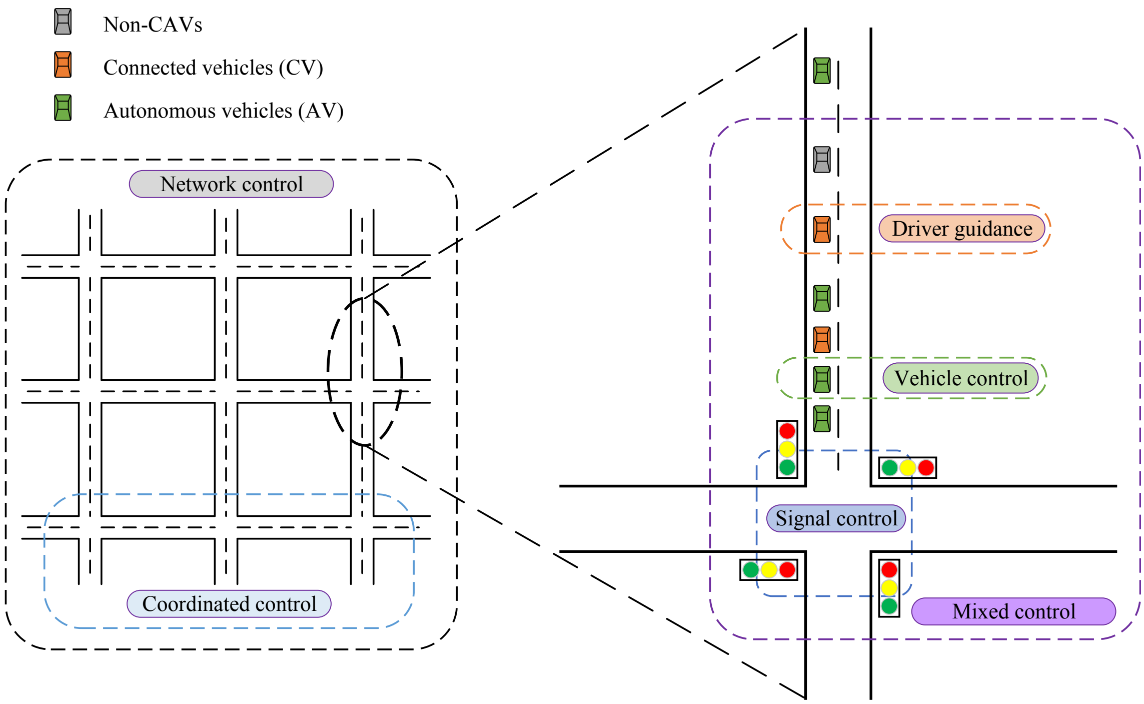

Fig. 3. Traffic control of urban intersections.

of corridors and networks. Based on single intersection control, we will discuss CAV-based signal coordination on traffic corridors. Research on network-wide CAV signal control is relatively sparse in the current literature, for which we will provide some discussions in Section 4.

For CAV-based single intersection traffic control, there are generally three types of control methods, depending on the availability of vehicle automation and/or V2X:

- Based on signal and vehicle data, the driver guidance control system can provide instructions to drivers on how to properly operate the vehicles to achieve certain objectives (e.g., minimizing fuel consumption, reducing travel times, etc.). Under the automated vehicle (AV) environment, these driving operations may be executed automatically, which can help achieve more improved control performances.
- Under the CVs environment, the signal control system can optimize signal timing and phases based on CVs data to improve the performance of intersection traffic. Typically, actuated signal control, platoon-based signal control, and planning-based signal control are included in this category. Actuated signal control can adjust signal timing and phases based on current traffic states and does not apply prediction, while platoon-based and planning-based methods will predict future traffic flow states to generate optimal signal timing plans. Platoon-based control groups the incoming vehicles into platoons, while planning-based methods usually treat each vehicle individually.
- Under the CAVs environment, the signal-vehicle coupled control (SVCC) system can optimize the vehicle operations and signal timing/phases simultaneously to achieve better traffic control performances.

Generally, as pointed out in Li et al. (2014c), we can formulate a general arterial traffic control problem as an optimization problem, in which the state variables are denoted as $x(k)$ and the environment inputs are denoted as$d(k)$. The objective is to optimize a certain performance index J over a finite time horizon $[0, K]$. J is usually mobility-based or sustainability-based objectives or the combination of the two. The decision variables are a sequence of control inputs $u(0), u(1), \cdots u(K)$. Constraints include initial conditions, traffic flow dynamics, and vehicle dynamics. The state variables, environment inputs, control inputs, and constraints would be different for different control methods, for which details are provided in Table 2 (attached at the end of this paper). This optimization problem is denoted as A1 in this paper, which can be conceptually expressed as follows.

Problem A1:

$$\min_{u(k)} J = f[x(K)] + \sum_{k=1}^{K} g[x(k), u(k), d(k)] \tag{1}$$

subject to

(i) State equation

$$x(k+1) = x(k) + h[u(k), d(k)],\ k = 1, \cdots K-1 \tag{2}$$

(ii) Initial and end state conditions

$$x(1) = x_0,\ x(K) = x_K \tag{3}$$

(iii) Constraints of state, environment and input variables

$$\varphi[x(k), u(k), d(k)] \in \Omega,\ k = 1, \cdots K \tag{4}$$

where $f[.]$, $g[.]$, $h[,]$ and $\varphi[.]$ are certain functions, $\Omega$is a set of values.

We should note here that the general optimization model A1 likely involves binary or integer variables (e.g., to indicate whether the current phase is red or green; see Li and Ban (in press) and the dimension of the problem can be quite large especially when we consider individual vehicles' performances such as emissions or fuel consumption. Certain approximation or reformulation techniques (such as dynamic programming) or distributed methods were often applied to reach a satisfactory solution of A1 within a limited computational budget; see Feng et al. (2015). As shown in Table 2, this general optimization problem A1 can be specified to three types of control methods. In the follows, we will discuss them in detail.

3.1. Advanced driver guidance based on CAVs

For this type of control methods, the state variables become the vehicle speeds and positions, which follow the equations of vehicle dynamics or traffic flow models (such as car-following models). The control inputs are the vehicle accelerations and turn angles. The environment inputs become the signal timing and phases. All the variables are constrained by certain conditions, e.g., the physical limits of accelerations, speeds, and turn angles. The optimal solutions are speed guidances dedicated for certain objectives, such as to avoid being caught by red lights (Li et al., 2012) or save fuel by driving in economic modes (Katsaros et al., 2011; Schuricht et al., 2011; Tang et al., 2018; Ubiergo and Jin, 2016; Wu et al., 2010). These driving strategies may also be executed by automated vehicles, which can reduce the uncertainty of compliance of human drivers and help improve the control performance.

Reducing fuel consumption is one of the most important objectives of the driver guidance techniques, which is also called Eco-

Table 2
Summary of traffic control methods.

Control methods		Signal control with CVs		Driver guidance and AV control with signal information	SVCC
		Actuated and planning based	Platoon based		
State variables $x(k)$		Queue length, travel time		Vehicle speed, position	Queue length, travel time, Vehicle speed, position
Environment inputs $d(k)$		Arrival vehicles	Arrival platoon	Signal timing, phases	
Control inputs $u(k)$		Signal timing, phases		Vehicle acceleration, turn	Signal timing, phases, Vehicle acceleration, turn
Objective function J: mobility, fuel, emissions, and safety	Single intersection	$\min_{u(k)} J = f[x(K)] + \sum_{k=1}^{K} g[x(k), u(k), d(k)]$			
	Arterials and networks	$\min_{u(k)} J = \sum_{n=1}^{N} \{f[x(K)] + \sum_{k=1}^{K} g[x(k), u(k), d(k)]\}$ *Centralized* $\min_{u(k)} J = f[x(K)] + \sum_{k=1}^{K} g[x(k), u(k), d'(k)]$ *Distributed* where $d'(k)$ consists of the information of other intersections			
State equations $x(k+1) = x(k) + h[u(k), d(k)]$		Queueing models, LWR, car-following models		Vehicle dynamics, car-following models	Traffic flow models, vehicle dynamics, car following models
Initial and end state condition $x(1) = x_0, x(K) = x_K$		Start and target queue length or travel time (e.g. dispatch all vehicles in the queue)		Start and target speed and position	Start and target queue length, travel time, vehicle speed and position
Constraints of state, environment and input variables $\varphi[x(k), u(k), d(k)] \in \Omega$		Maximum queue length, cycle length, green signal length; no interrupt phases etc.		Physical acceleration, speed, and turn angle limits etc.	All constraints of the former two methods
Published works		Beak et al., 2017; Gradinescu et al., 2007; Feng et al., 2015; Hu et al., 2016; Islam et al., 2017; Li and Ban, 2017	He et al., 2012; Lioris et al., 2017; Pandit et al., 2013; Xie et al., 2011	Katsaros et al., 2011; Li et al., 2012; Schuricht et al., 2011; Tang et al., 2018; Ubiergo and Jin, 2016; Wu et al., 2010	Guler et al., 2014; Li et al., 2014a; Sun et al., 2017; Xu et al., 2017; Yu et al., 2018

driving guidance and is believed to have the potential of saving fuels from 5% to 15% (Van Mierlo et al., 2004). Different Eco-driving guidance algorithms may concentrate on different considerations: for examples, driver behaviors like lane changing and vehicle platooning, road structures like single/multiple intersections, traffic states like surrounding traffic and mixed traffic. Rakha and Kamalanathsharma (2011) proposed a rule-based Eco-driving strategy at signalized intersections based on the V2I communication. They used a real-world data based statistical emission model that consists of linear, quadratic and cubic combinations of speed and acceleration levels to describe fuel consumption. Integrated with the vehicle dynamics model and the information of signal phases and timings, the rule-based Eco-driving model was then designed to optimize fuel consumption by providing speed profiles. The objective J is the total fuel consumption, which is calculated by the vehicle speed (state variable x) and acceleration (control variable u). The information of signal phases and timings serve as the environment inputs d. The vehicle speed follows the vehicle dynamics and also the constraints of the vehicle's physical limitations. Together, an approximate minimization of the objective function was achieved by the rule-based controller. While Rakha and Kamalanathsharma's work focused on a single intersection, Boriboonsomsin et al. (2012) extended the Eco-routing guidance to the entire trips of a vehicle, which is also known as Eco-routing. They used a dynamic roadway network database to integrate and store historical and real-time traffic information. In addition, they used a hybrid method that combines the microscopic energy model with a large vehicle activity database to create the relationships between link-based energy factors and the link-based explanatory variables. Based on such relationship, they estimated the energy/emission operational parameter set by a multivariate regression method. The Dijkstra algorithm was then used to build the routing engine to search the shortest paths based on different objectives. The evaluation results showed that the eco-routes could generate about 13% fuel savings while the travel time might slightly increase.

Apart from fuel consumption, other objectives like those related to mobility may also be considered when designing driver guidance algorithms. For this, integrating multiple objectives in one algorithm is a promising direction. Katsaros et al. (2011) proposed a rule-based green light optimized speed advisory (GLOSA) algorithm to reduce fuel consumption and meanwhile improve traffic efficiency. The key idea of the method is to reduce the stop time at intersections. Their algorithm firstly calculated the distance and travel time to the front traffic signal, then calculated the target speed based on the rules that were predefined considering different signal phases at the estimated arrival time. The advisory speeds were then presented to drivers via V2X. Assuming that drivers would follow the advisory speeds, they built an integrated cooperative ITS simulation platform and tested their algorithm under different CAVs penetration rates. The results showed that the proposed method could improve fuel consumption by up to 7% and reduce stop time up to 80% at intersections.

Since drivers usually cannot perfectly follow the advisory speeds in reality, the effectiveness of the proposed methods needs to be proven in real traffic scenarios. To the best of our knowledge, some research groups and government agencies have conducted field experiments to evaluate the driver guidance systems. For example, the GLOSA system has been tested by field experiments in the city of Ingolstadt, Germany (Bodenheimer et al., 2014). The fuel-saving oriented driver guidance platform "Glidepath Prototype system" has also been developed and tested through extensive field experiments, of which the results showed a 17% fuel improvement on average (Altan et al., 2017). However, it should be pointed out that many existing studies about driver guidance systems were only tested in simulations. More efforts on real-world applications and testing of such systems need to be done in the future. In addition, the vehicle dynamics models and traffic models used in those methods were usually oversimplified, making the results less convincing. We expect more research studies can focus on this direction in the future to provide more empirical testing/validation results.

3.2. Advanced traffic signal control with CAVs

For advanced traffic signal control with CAVs, the state variables of the general optimization problem A1 become the queue length, travel time, or other performance measures, which should also follow the state equations like queueing models, LWR models, and car-following models. The control variables are the signal timing and phases. The environment inputs become the arrival vehicles for actuated and planning-based control, and arrival platoons for platoon-based control. These variables should also follow proper constraints such as the cycle length, and maximum and minimum green times. The CAV-based traffic signal control methods are usually designed first for isolated intersections, and then extended to corridors, and even networks, along with the modification of the objective function to consider the coordination of all the intersections.

There are two methods to derive the objective functions of corridors and networks. One is the centralized methods, which formulate the optimization problem by summing all the objectives of the intersections or defining a common objective such as throughput. The other one is the distributed methods, which usually assume the traffic information of neighboring intersections is known as an environment input. The distributed methods can lead to reduced computation burden, which, however, may not help achieve the global optimization results.

According to the control schemes, we can further divide advanced CAV-based traffic signal control into three types: *actuated traffic signal enhanced using CAVs data*, *platoon-based traffic signal control based on CAVs coordination*, *planning-based traffic signal control based on CAVs coordination* (including *transit priority traffic signal control enhanced by CAVs coordination*). The resulting Problem A1 might be slightly different for these different control types. For example, the actuated traffic control may only extend or reduce the green time according to the estimated current volume, while the planning based method would optimize both signal timing and phases in a particular forward time horizon.

The key difference among these three control methods is in what detail they predict the future traffic states. Enhanced by CAVs data, actuated (adaptive) traffic signal control would estimate the current traffic states (e.g., queue length) and predict some relatively rough and aggregated traffic measures (e.g., average volume) in the future, based on which the control decisions (e.g., extend or terminate certain phases) could be generated. The platoon-based signal control would simplify the problem by categorizing individual vehicles to platoons and predict their arrivals/trajectories, which could make it easier to adjust the timing plan. The planning-based signal control would take the detailed trajectories of individual vehicles into account and optimize the signal timing/phases in a forward time horizon by adopting more accurate and complex models. The traffic flow dynamic models and optimal control strategies usually become more exquisite when the control methods come from actuated to planning-based, while on the other hand, the robustness and flexibility would also decrease.

3.2.1. Actuated traffic signal control enhanced by CAVs data

Actuated signal control can dynamically adjust the timing parameters to respond to real-time traffic arrival changes. Since many existing studies considered prediction of traffic flow based on CAVs data, this kind of control is also called adaptive traffic signal control in the literature. This generally results in more efficient utilization of intersection capacity than fixed-time signal control in which signal phases and cycle lengths are pre-selected based on historical traffic patterns (Roess et al., 2011; Zhang and Wang, 2011).

Conventional actuated traffic signal control systems collect traffic information via inductive loop detectors that are usually installed tens of meters upstream to the stop lines. The obtained information is inaccurate and limited spatially. As a result, certain relatively rough models have been developed to describe traffic flow states which often fail to well present the variability in traffic demand and vehicular inter-arrival times (Yin et al., 2007; Yun and Park, 2012; Zheng et al., 2010). CAVs provides a remedy for such problems (Day and Bullock, 2016; Goodall et al., 2013; Gradinescu et al., 2007; Kari et al., 2014; Li et al., 2014c; Wu et al., 2015; Younes and Boukerche, 2016). Based on the accurate position information of the arriving vehicles, we can either extend/shorten the current phase or add an extra phase to make on-time changes.

For example, Gradinescu et al. (2007) proposed an actuated traffic signal control system based on CVs. The information of vehicles within a few miles range around an intersection were collected by the V2I and infrastructure to infrastructure (I2I) communication techniques. They first used these data to estimate the demand volume of each approach per cycle, and then calculated the optimum cycle length using the Webster's formula (Chaudhary et al., 2002). The green time was allocated to produce equal degrees of saturation on each link. The preliminary signal plan for the next cycle was generated during the current cycle and adjusted to meet practical limitations like the minimum and maximum cycle lengths and pedestrian minimum green times. They tested the system in simulation based on two real-world major intersections. The experiment results showed that the system could reduce traffic delay and fuel consumption compared with traditional pre-timed traffic signals. In this work, the estimated demand volume is the state variable x and the information of vehicles around the intersection serve as the environment inputs d. The objective function J is the equality of the degrees of saturation on each link, which is maximized by generating optimum cycle length and allocating green times proportionally.

The CAVs based actuated traffic signal control is essentially a passive method since it adjusts the signal plan according to the estimated traffic states without detailed predictions of future traffic conditions. From the optimal control point of view, the strategies generated by the actuated control may not be optimal in long-term since future traffic conditions are not considered. Compared with other methods, the main advantage of actuated control is that its computation burden is relatively light due to the smaller number of control variables as well as the simpler traffic models. The fixed sensor based actuated signal control has been widely used in real-world traffic management. This makes it more practical to implement the CAV-based actuated signal control in practice compared to other advanced control methods.

It should also be pointed out that most existing studies in this direction only considered isolated intersections. Although coordinated actuated signal control systems using information collected from fixed sensors once received noticeably attentions (Yin et al., 2007; Yun and Park, 2012), their V2X-based modifications have not been well studied. We expect more research efforts may be carried out in this direction when CAVs become more pervasive in the near future.

3.2.2. Platoon-based traffic signal control based on CAVs coordination

Actuated traffic control relies more on prevailing real-time traffic information and does not require too much future traffic conditions (i.e., traffic prediction). In contrast, traffic prediction is essential to platoon-based traffic signal control (and also planning-based control). By identifying the platoons (or categorizing individual vehicles into pseudo platoons) and predicting their arrival time in advance, the platoon-based signal control aims to schedule the signal timing plans to allow the platoons to pass the intersections without severe interruptions, which can increase the overall traffic efficiency. Although the idea of platoon-based traffic signal control has been proposed for several decades (Mirchandani and Head, 2001), it became realistic only after V2X technique was introduced (He et al., 2012; Liang et al., 2018; Lioris et al., 2017; Xie et al., 2012). This is because V2X makes it possible to properly identify platoons so that platoon-based optimal signal timing plans can be generated accordingly.

Pandit et al. (2013) proposed a platoon-based "oldest arrival first" traffic signal control method to reduce delays at a single intersection. They reduced the traffic signal control problem to a job scheduling problem by enforcing that all jobs require equal processing time. The conflicts between jobs and the objective of minimizing job latency values were modeled as a two-competitive algorithm. After collecting real-time speed and position information of sample vehicles through vehicular ad-hoc networks (VANETs), they grouped the vehicular traffic into approximately equal-sized platoons by searching all possible platoon configurations to minimize the difference between the maximum and minimum required processing time. The grouped platoons could be scheduled by solving the reduced job scheduling problem. The algorithm was tested under different approach arrival rates and penetration rates. Compared with traditional Webster's method and vehicle-actuated control method, the proposed method could significantly reduce delays when the traffic inflow rates are not large. The experimental results also showed that the proposed method did not perform well under low penetration rates, since the arrival rate cannot be accurately estimated under low penetration conditions. In this work, the speed and position information of sample vehicles serve as the environment input d, which are further processed to be the arriving platoons. The state variable x is the travel time of the vehicle platoons and the control variable u is the signal timing and phases. The objective J is the total delay at the intersection experienced by all vehicles, which is minimized by adopting the optimal control variables generated by the "oldest arrival first" method.

While Pandit et al. (2013) focused on a single intersection, He et al. (2012) presented a platoon-based multi-modal dynamical progression model to control arterial traffic signals. Sample vehicle data were first used to identify existing queues and platoons approaching each intersection by a headway-based recognition algorithm. Then, they formulated the traffic signal control problem into a mixed-integer linear program (MILP) based on the calculated platoon information, current signal status, and priority requests of special vehicles. By using platoon data instead of individual vehicle data, they reduced the number of integer variables of the MILP, making it relatively easier to solve. Their model can deal with both under-saturated and over-saturated traffic conditions. The proposed method was tested in VISSIM simulations. Results showed that, under a 40% penetration rate, the method could reduce the overall average delay of two traffic modes (i.e. automobiles and transit buses) by 8% compared to the coordinated actuated signal control method optimized by SYNCHRO.

Xie et al. (2011) proposed a platoon-based self-scheduling algorithm for real-time traffic network signal control. First, the sensed traffic data were used to aggregate incoming vehicles into critical platoons and anticipated queues based on the non-uniformly distributed nature of traffic flows. Each intersection was controlled by a self-interested agent with the knowledge of platoon information of neighboring intersections. Based on the information of currently anticipated queues and incoming platoons from other intersections, the self-scheduling algorithm generated two possible actions (i.e., to extend or terminate the current phase) within each decision rolling horizon, aiming to keep vehicles moving rather than simply clear the queues. The proposed method was tested on two traffic networks with dynamic vehicle flows. Compared to the pre-timed method, queue-clearing based adaptive method, and Webster-based method, the proposed method performed the best considering the control performance of bottleneck intersections and the coordination performance of vehicle flows.

Compared with actuated signal control, platoon-based signal control using CAV data could achieve better performance since it could forecast some mid-level traffic flow states (i.e., the volume and arrival time of platoons) and make the best control decisions accordingly. Meanwhile, aggregating vehicles into platoons could reduce the computation burden, making it more practical to be implemented in the real world. However, the method may only generate sub-optimal strategies due to this simplification. Besides, the performance of platoon identification algorithms may significantly affect the performance of the method. How to define, model, and aggregate platoons from real traffic flows needs further investigations.

3.2.3. Planning-based traffic signal control based on CAVs coordination

Platoon-based methods categorize the incoming vehicles as platoons and ignore the inner dynamics and disturbances among vehicles in the same platoon. On the contrary, planning-based methods treat all vehicles at the same level, which can better describe the real traffic condition. Besides, platoon-based methods usually directly assume known arrival distributions (e.g., Poisson or uniform arrivals), or estimate the arrival time of the platoons and assume uniform arrivals within each platoon. Planning-based methods often estimate the actual arrival time of every vehicle and predict traffic conditions in a forward time horizon.

Planning-based control has been widely studied by many researchers (Goodall et al., 2013; Lee et al., 2013). The optimization model of planning-based control is usually an integer nonlinear programing problem and hard to solve especially when individual vehicles' trajectories are considered (Li and Ban, in press). Certain approximation and reformulation methods are usually applied. Dynamic programming (DP) is one of the most commonly used techniques to reformulate and solve such control problems (Chen and Sun, 2016; Feng et al., 2015; Sen and Head, 1997). For example, Feng et al. (2015) proposed an optimization-based real-time traffic signal control method in a CV environment. Assuming known vehicles' speeds and positions, they first separated the upstream roads into three regions (i.e. free-flow, slow-down, and queuing) and estimated the status of unequipped vehicles. Based on such information, they constructed a complete predicted arrival table for each phase for a certain (future) time horizon. Then they built a two-level optimization model. The upper level generates the minimum and maximum allowable barrier group lengths by DP, and the lower level is formulated as a utility minimization problem with two alternative objectives (i.e., minimizing total vehicle delay and queue length respectively). The outputs of the model are the optimal signal timing and phases. They tested the method by modeling a real-world intersection in VISSIM. The results showed that the method can reduce the total delay by 16.33% under high penetration rate compared to the fully actuated control method, which however generated the same delay under low penetration rates. In order to make the DP method more practical and efficient, Li and Ban (2017) proposed a DP based method to minimize both fuel consumption and travel time considering a fixed cycle length. They first formulated the signal control problem as a mixed integer nonlinear programing problem, and then reformulated the problem as a DP model by dividing the timing decisions into stages (one stage for a phase) and approximating the fuel consumption and travel time of a stage as functions of the state and decision variables of that stage. By adding the end-stage cost and a branch and bound regulator to the DP formulation, the resulting optimal solution can be guaranteed to lead to the fixed cycle length. Simulation results showed that the proposed method could generate optimal solutions that lead to the fixed cycle length. The control performance was improved compared to the actuated control methods and was similar to the results by a global mixed integer nonlinear programming (MINLP) solver in MATLAB. In this work, the objective J is the weighted summation of total system travel times and fuel consumption. The state variables x are the vehicle trajectories which are modeled by the intelligent driver model (IDM). The signal timing and phases serve as the control variables u. The constraints include man/min green time, fixed cycle length, and the physical limitations of vehicles. The objective function is minimized by DP, which also generates the optimal control variable in real-time.

Compared to other control methods, planning-based methods are harder to be implemented for real-time arterial or network control due to the high complexity of the optimization models. Another reason is that even with CVs, we still need to predict vehicles volumes, delays, speeds, or queue lengths in order to optimize signal timing. Such predictions are mutually dependent on signal timing, making the problem a complex, integrated optimization problem. This is particularly true for corridor level or network level control. Beak et al. (2017) proposed a two-level optimization method for corridor level signal control. At the intersection level, they used DP to allocate the optimal green time to each signal phase by considering the coordination constraints. At the corridor level, they formulated a mixed integer linear program based on the information of individual intersections to generate the optimal offsets, which were then sent to the intersection level as the coordination constraints. Simulation results showed that the proposed algorithm can reduce the average delay as well as the number of stops for a corridor compared to conventional actuated-coordinated signal control methods. Similarly, Li and Ban (under review) formulated the corridor signal control problem as a centralized MINLP considering the fixed cycle length constraint to reduce both fuel consumptions and travel times. The MINLP was decentralized to a two-level model: At the intersection level, the phase durations were optimized by a DP algorithm initially proposed by Li and Ban (in press). At the corridor level, the optimal offsets were updated by the MINLP using the optimal phases generated at the first level. They tested six cases considering different demands, and the simulation results showed that the performance of both major and minor streets improved under high traffic volumes.

The above methods are centralized approaches, which are not efficient when solving large-scale problems. In order to reduce the complexity and computation burden of network-wide optimization problems, the distributed control has been receiving more attention recently. Diakaki et al., 2014; Islam et al., 2017 presented a distributed coordinated signal control method in the CV environment. They reformulated the optimization problem from a centralized architecture to a decentralized form, which can reduce the computation complexity and make it possible for real-time applications. The key idea of the method is to maximize the intersection throughput while penalizing for queue lengths. Given the information of neighboring intersections, the distributed algorithm can coordinate with each other to avoid finding local optimal solutions. Simulation results showed that the method could increase the throughput by 1–5% compared to the actuated coordinated signal control method in VISTRO, and reduce travel time by 17–48%. Another decentralized signal control technique is based on the backpressure concept, which was initially applied to communication and power networks and was recently applied to traffic signal control (Gregoire et al., 2014, 2015; Le et al., 2015; Wongpiromsarn et al., 2012). The backpressure method is completely distributed over intersections such that the complexity of the problem could be dramatically reduced. For example, Wongpiromsarn et al. (2012) proposed a distributed traffic signal control algorithm based on backpressure to maximum the network throughput. They defined "pressure" as the current flow rate of the traffic movement weighted by the difference between the queue lengths on the two corresponding movements. After calculating the pressure of each phase, the algorithm selected the phase with the highest pressure for the current intersection. Each intersection only requires the information of its own and adjacent intersections, and no global view is needed. They also proved mathematically that the method could help achieve the maximum network throughput. Simulation results showed that this method performed significantly better than traditional adaptive signal control methods.

Planning-based signal control could predict future traffic states and find the optimal solution within certain forward time horizon, which makes it more desirable. However, the computation cost might be high due to the resulting complex optimization problem, especially when dealing with large-scale networks or considering different movements of vehicles. In addition, the prediction horizon needs to be carefully selected. The longer the prediction horizon is, the more future information it could utilize, while the computation burden and the prediction errors may also increase. On the contrast, shorter prediction horizon could make the computation faster but may decrease the control performance due to the lack of future traffic information.

3.2.4. Transit priority control based on CAVs

Transit priority signal control is a special case of planning-based signal control, which is also one of the most important topics of multi-modal traffic control. We thus review it separately in this subsection. Transit priority control aims to reduce the delay of transit vehicles by adjusting the signal timing and phases. Based on the priority requesting time and current signal phase, there are generally four strategies that conventional transit priority control can adopt: (1) extend the green time if the current phase is green; (2) add an extra green phase if the current phase is red; (3) change back to the green phase if the current phase is yellow; and (4) run the green phase earlier if the current phase is red (Diakaki et al., 2014). However, conventional methods usually break traffic progressions and cause a significant delay of the competing traffic flow. Some advanced transit priority control methods have been invented to overcome these shortcomings (Balke et al., 2000; Ekeila et al., 2009; Liao and Davis, 2007). For example, Balke et al. (2000) proposed and tested an intelligent bus priority concept at signalized intersections without disrupting normal traffic progressions. They firstly estimated the arrival time of the bus at the bus stop and at intersection stop line to identify whether the bus is on schedule, which was used to determine the priority. The best priority strategy was then selected after comparing the performances of different strategies (phase extension, phase insertion, and early return) based on the arrival time. The method then adjusted the sequences and durations of the traffic signal phases so that the bus could pass the intersection at the green time.

Among these advanced transit priority control methods, more and more recent studies utilized CAVs to build efficient algorithms (Hu et al., 2015; Wu et al., 2016, 2018; Yang et al., 2018; Zeng et al., 2015). CAVs could not only provide the control system with more accurate and richer data, but also make it possible for the drivers to be guided by the optimal solution to reduce the overall delay. For example, Hu et al. (2016) proposed a person-delay-based optimization method for intelligent transit signal priority (TSP) control, which can resolve multiple conflicting TSP requests at a single intersection. When multiple buses were detected and conflicting requests were generated based on the predicted arrival times, the TSP timing plan optimization problem was formulated as a binary mixed integer linear program with the objective to minimize per-person delays and solved by a standard branch-and-bound routine. Meanwhile, the recommended speed can be generated and provided to all the TSP buses. The method was evaluated by both analytical and microscopic simulations. The results showed that the proposed TSP control method could reduce the average bus delay up to 48% compared with the conventional first-come-first-serve TSP methods.

How to build an effective transit priority control system without causing noticeable delays on the whole system is an important problem to be further studied. There are several promising directions to achieve this goal. The first one is to reduce the delay caused by conflicting priority requests. Most current studies adopted the first-come-first-serve strategy to resolve conflicting requests, which has been found to possibly increase the total system delay (Zlatkovic et al., 2012). New techniques such as simultaneous TSP accommodation have been proposed (He et al., 2014; Hu et al., 2016). However, more efforts need to be conducted, e.g., the selection of the accommodation weights and the sensitivity analysis of the uncertainties. The second one is to improve the efficiency of transit priority control by reducing the delay of the competing traffic. For example, in order to reduce the negative impact of the priority signal algorithm on passenger cars, Zamanipour et al. (2016) proposed an analytical model and the corresponding multi-modal intelligent traffic signal system (MMITSS). Simulations based on real-world traffic networks showed that MMITSS could provide optimal signal schedules that minimize the total weighted delays. In addition, the idea of SVCC (see the next section) has been implemented in transit priority control and has been shown as a promising solution. This kind of control system could guide the bus drivers to follow certain velocity profiles as well as adjust the signal timings and phases, by which the control errors and system delays could be significantly reduced (Hu et al., 2016; Seredynski et al., 2015; Seredynski and Khadraoui, 2014).

3.3. Signal vehicle coupled control (SVCC) based on CAVs

Traffic signals and vehicles were traditionally studied separately. In traditional traffic signal control systems, the characteristics of individual vehicles were almost never considered. However, signal control and vehicle control are mutually dependent in reality: signal timing influences the movements of individual vehicles and thus the performances (such as emissions and fuel consumption) of the vehicles, while at the same time individual vehicle performances are the critical input to traffic control methods on how to best adjust signal timing.

In the past, however, the information exchange between vehicles and signals were quite limited: signals detect the arrivals of vehicles (often as the aggregated number of vehicles in a certain time window) and adjust signal timing accordingly (and often reactively), while vehicles/drivers see the signal timing and adjust driving accordingly when they are close to the intersection. This makes it impossible to implement coupled signal and vehicle control.

With CAVs, information between signals and (individual) vehicles can be exchanged in real time, which should be leveraged to further improve the traffic control performance, leading to the SVCC (Guler et al., 2014; Sun et al., 2017; Xu et al., 2017; Yang et al., 2016; Yu et al., 2018). For this problem, the state variables of the general problem A1 become the queue length, travel time, vehicle states (such as throttle and exhaust system states, and battery state of charge if electric vehicles are considered), which should follow proper state equations such as traffic flow models and vehicle dynamic equations. The control inputs are the signal timing and phases, vehicles operations (such as turn angle, gas pedal, etc.). These variables should be constrained by proper constraints related to both signals (such as minimum/maximum green times, cycle lengths, etc.) and traffic flow (such as car following models). In general, the optimization model for SVCC is more complex, involving both linear and nonlinear states, discrete and continuous control inputs, and other complex constraints, making the problem much more challenging to solve.

Research on SVCC has just gained attentions. For example, Li et al. (2014a) developed a signal control algorithm for automated vehicles at isolated signalized intersections. The method can simultaneously optimize vehicle trajectories and signal timing plans. By considering only two phases of the traffic signal, they used a simple enumeration method to select the optimum signal timing plan. They first determined the trajectory of the first vehicle, then calculated the trajectories of the following vehicles, and finally assigned the vehicles to different cycles by checking whether a vehicle can depart the intersection before the end of the green. A rolling horizon scheme was developed to implement the algorithm and to process newly arriving vehicles continually. Simulation results showed that the proposed algorithm can reduce the average travel time delay by 16.2–36.9% and increase the mobility by 2.7–20.2% compared to traditional actuated signal control methods.

Xu et al. (2017) proposed a cooperative control method to simultaneously optimize traffic signal timing and vehicle operations to improve transportation efficiency and vehicle fuel economy. The method considered multiple objectives: safety, mobility, and energy use. For this, the modeling/control framework of the paper defined different priorities for different objectives: safety first, mobility second, and energy third. Accordingly, they proposed to solve safety by design, i.e., by applying the classical "dual-diagram" signal control design, improve mobility by optimizing signal phases and timing to minimize the total travel time of all vehicles, and save energy by optimizing the trajectory of each vehicle given its time budget to pass the intersection (obtained via solving the mobility objective). The proposed approach thus decomposed the complex control problem into three (much simpler) sub-problems based on the priorities of the three main objectives. Cooperating with each other, these three sub-problems were solved sequentially. Simulation results in MATLAB and VISSIM showed that the proposed method could improve traffic efficiency by 19.7% and fuel economy by 23.7% compared to a benchmark actuated signal control algorithm. The main contribution of Xu's work is its useful insight on how to consider different important objectives of SVCC with CAVs in general. In this work, the vehicle speed and position are the state variables x which follow the vehicle dynamics. The control variables consist of signal timing/phases and vehicle accelerations. The objective J includes the travel times and fuel consumptions, which are estimated by the car following model and fuel consumption model. The objective is minimized by solving the sequential sub-problems.

SVCC is relatively new but has great potential to improve traffic control performances. In addition, it may be relatively easier for SVCC to transfer to non-signal control (with proper safety guarantees) when 100% CAVs is achieved in the traffic system, which may further improve the performances of traffic control. Currently, many questions for SVCC still remained unsolved, e.g., how to efficiently combine signal and vehicle control, how to extend SVCC methods to control traffic corridors and networks, and how to apply the methods to real-world implementations. All those topics need to be further investigated.

4. Future research of CAV-based traffic signal control

In addition to the future research topics under each of the control methods discussed above (listed at the end of each subsection in Section 3), we summarize and discuss several important future research directions on CAV-based traffic signal control in this section.

4.1. Network control

The current CAV-based control methods mainly emphasized on single intersections, and only a handful of them discussed corridor-level signal optimization and coordination. CAV-based network traffic control, however, has not been extensively studied. The key challenges of CAV-based network control, beyond what has been discussed so far for single intersection and corridor control, are how to coordinate multiple intersections by leveraging CAVs and how to solve the resulting large-scale problems efficiently. These problems all require further and dedicated investigations.

For example, distributed control may be helpful in solving large-scale CAV-based network control by decomposing the network control problem into small sub-problems each for an intersection or a small number of intersections. The sub-problems can share information with each other and be solved more efficiently (Islam et al., 2017; Wongpiromsarn et al., 2012). So far, most centralized network-level control to distributed control decomposition methods were heuristic (Islam et al., 2017Islam and Hajbabaie, 2017; Mckenney and White, 2013; Mehrabipour and Hajbabaie, 2017). Few of the current studies on how to guarantee the global optimality of distributed traffic signal control and how to analyze the stability/sensitivity issues of the decomposition process. For this, researchers might benefit from the distributed control techniques that appear in other fields like computer science and automatic control (Cao et al., 2013). For example, the decomposition approach for identical dynamically coupled sub-systems (Massioni and Verhaegen, 2009), the distributed control design principles for spatially interconnected systems (D'Andrea and Dullerud, 2003), and the distributed model predictive control and stability analysis techniques (Camponogara et al., 2002) that could all provide useful insights for the topic of distributed network-level traffic signal control.

Another promising network traffic control method is the hierarchical control technique that considers a multi-level optimization problem. Most hierarchical approaches made macroscopic regional level decisions (like perimeter control) at the upper level, and microscopic intersection level decisions (like specific signal phases and timings) at the lower level. One key technique of hierarchical traffic control is to define the macroscopic and microscopic models. Traffic flow models such as the macroscopic fundamental diagrams (MFD; see Daganzo et al., 2012; Geroliminis and Daganzo, 2008; Yang et al., 2017) may be of great promise for modeling the macroscopic traffic. MFD can guide the division of the network (into regions) and construct the upper level problem (for the entire network) and the lower level problems (for individual regions). Most current works on MFD-based traffic control focused on regional-level perimeter control (Geroliminis et al., 2013; Haddad et al., 2013). How to integrate the MFD based network control with more detailed intersection/corridor control under the CAVs environment remains largely open. In addition, current MFD based network control rarely took CAVs to consideration. Researchers usually assumed full knowledge of the accumulation of vehicles, which is not applicable when CAVs have not reached 100% penetration. How to estimate the vehicle accumulations under limited CAVs penetration rate is one of the important topics, which the research community has just started to explore (Yang, 2018). Other critical issues such as the consistency between the upper level problem and the lower level problems, and the priority on different vehicle types merit further investigations. Future studies may focus on those and other critical issues of CAV-based network control, including network decomposition, information sharing, cooperation methods, and computation efficiency.

4.2. Impact of CAVs penetration and level of automation

The penetration rate of CAVs can significantly influence the performances of the above traffic control methods (Ferman et al., 2005; Jenelius and Koutsopoulos, 2015). Many existing studies assumed 100% penetrations of CVs and/or AVs with full automation (i.e., level 5) so that the full information of all vehicles can be used and/or all vehicles can be controlled to better design the traffic control methods (Islam et al., 2017; Li and Ban, 2017; Li et al., 2014a; Xu et al., 2017). The main advantage of assuming 100% penetration is that we can avoid estimating the information of unequipped vehicles, which can significantly reduce the complexity of the resulting model and estimation errors.

Although it is expected that the penetration rate of CAVs may dramatically increase in the future, there is still a long way to achieve such a goal of high CAVs penetration or fully automated vehicles. Therefore, it is practical and important to consider different levels of CAVs penetration and vehicle automation, i.e., to consider mixed traffic flow with both human-driven vehicles and AVs, with and without connectivity, and with different automation levels, when designing CAV-based traffic control methods in practice.

For the purpose of traffic signal control, the traffic flow states including travel times, queue lengths, and volumes are the most important measures. Usually, we do not need to track every vehicle to accurately predict the future traffic flow states. Although specific algorithms requiring lower penetration rates have been investigated (Zheng and Liu, 2017), most current results indicated that the performance would undergo a significant change when the penetration rate becomes larger than 25–30% (Ban et al., 2011; Hao et al., 2014). However, we still do not know the exact phase transition point (i.e., the critical penetration rate) for all the scenarios, since there are too many factors that may influence the signal control performances.

A few existing studies (Argote-Cabañero et al., 2015; Beak et al., 2017; Day and Bullock, 2016; Feng et al., 2015; Rios-Torres and

Malikopoulos, 2018; Validi et al., 2018) had begun to discuss the relationship between CAV penetration rates and various performances of the control algorithms. For example, Day and Bullock (2016) explored the relationship between CVs penetration and the performance of the signal offset optimization algorithm of a corridor. They found that the offline optimization algorithm over a 3-hour window could perform well with a CV penetration as low as 1%, while the online optimization with 15-min windows requires at least 5% CV penetration. Validi et al. (2018) studied the impact of different V2V communication and ADAS penetration rates on road safety. The simulation results under six different scenarios showed that a 40% V2V penetration rate could prevent all types of accidents. Argote-Cabañero et al. (2015) explored the relationship between the CV penetration rate and the accuracy of the estimation of arterial measures of effectiveness (MOEs) such as average speed, number of stops and delay. The minimum penetration rates required in order to yield acceptable estimations on different MOEs were generated based on simulations. Rios-Torres and Malikopoulos (2018) analyzed the impact of CV penetration on fuel consumption and traffic flow under different traffic volumes based on a merging on-ramp scenario. They showed that 100% CV penetration could improve the fuel efficiency under any traffic volume; in the mixed flow scenario, the fuel-saving benefits could be only achieved when the traffic volume is low.

These studies could serve as a good starting point, while more efforts need to be conducted. For example, more traffic scenario studies and real-world tests are urgently needed to build the relationship between the CAV penetration rate and different performance measures, and more efforts are needed to quantify the benefits of different levels of vehicle automation levels for traffic signal control, with or without V2X connectivity. In addition, current works usually adopted simulation models to study the impact of penetration. Whether there are theoretical models or theoretical-simulation mixed models that could better verify the impact of penetration on signal control performances should also be thoroughly studied.

4.3. Safety guarantees and balance of multiple objectives

Most of the CAV-based traffic control methods reviewed here were developed by optimizing certain mobility and/or sustainability objectives such as minimizing the total system travel time or fuel consumption. Ironically few studies have considered safety when designing traffic/vehicle control and optimization strategies.

For traditional traffic control, our first objective should be safety, followed by mobility and other objectives (such as sustainability) (Li et al., 2018a, 2018b). Safety is traditionally guaranteed by design: including the dual-diagram design scheme (Roess et al., 2004) and other associated techniques such as the conflict monitor embedded in traffic controllers. Mobility is usually considered by minimizing the total delays or travel times of all vehicles passing the intersection (e.g., for optimizing the timing of a single intersection), or maximizing the throughput or other related measures (for coordinating multiple intersections). The sustainability objective is often defined as the total energy consumption or emissions of vehicles passing the intersection (Jiang et al., 2017b).

There were two primary ways to deal with safety issue of CAV-based traffic control. The first way focused on 100% penetration of CAVs and set certain safe following distances or time gaps for vehicles which have conflicts along their driving paths (e.g., at a traffic intersection where there is no physical signal system). If we consider the framework proposed in the general Problem A1, the first way for safety is to add new constraints φ for safe distances or time gaps, while objective J could be mobility or other related objectives. However, safety may not always be guaranteed via such methods, since not all vehicles were CAVs (i.e., 100% penetration) in the foreseeable future; and the communications problems and the vehicle sensing faults may still introduce too much uncertainty.

The second way considered mixed traffic flow and assumed the presence of physical traffic signals at intersections. Most of them applied traditional safety design methods such as the dual-diagram design for signal timing plans. Such design methods can usually ensure safety. However, when the penetration of CAVs reaches certain levels, it is important to investigate whether these existing safety design methods are the most appropriate for CAVs. There may be other design methods that can achieve similar safety guarantees but are more efficient. In addition, most current studies have focused only on vehicular traffic and neglected bicyclists and pedestrians. When applied to real-world traffic, the safety (and mobility) of all traffic participants needs to be considered properly (The Verge, 2018).

Furthermore, many existing studies focused on only one objective, while simultaneously considering multiple objectives can improve the overall control performance (Xu et al., 2017; Zhao et al., 2018). The key challenges include: (1) how to select the specific and quantitative measures for different objectives; (2) how to integrate multiple objectives with different units into one function and balance them; (3) and how to design the constraints for different objectives. We expect that future studies can simultaneously consider safety, mobility and sustainability objectives for vehicles, bicyclists, and pedestrians when developing CAV-based traffic/vehicle control methods.

4.4. Testing and implementations in real world

Most existing studies applied simulations and limited field data to test the developed methods, which might be quite different from real-world traffic conditions. For traffic state estimation, observation errors are inevitable when applied to real traffic systems, which might cause bias and even failures of the theoretical methods. How and to what extent could the errors influence the accuracy and robustness of the models are important research topics. At the same time, real-world implementations need a large number of field tests, which might be time- and resource- consuming. For this, researchers could benefit from several large-scale CV/probe vehicle data collection platforms to conduct initial testing/validation of the methods, including the Next Generation Simulation (NGSIM) program (Alexiadis et al., 2004), Safety Pilot program (Henclewood et al, 2014), Mobile Century project (Herrera et al., 2010), the Connected Vehicle Pilot Deployment Program of the United States Department of Transportation (USDOT), and the GAIA open dataset (Chuxing, 2018).

To the best of our knowledge, real-world testing and validation of CAV-based traffic control methods discussed in Section 3 have just started. The advanced driver guidance system is the first one that has been tested in real world due to the fact that it is relatively easier to develop a driver interface than to actually modify traffic signal control. We have discussed the real-world applications of the advanced driver guidance system (e.g., Altan et al., 2017; Bodenheimer et al., 2014; Lee et al., 2017) in Section 3.1. More efforts still need to be done to verify this and other advanced traffic signal control methods based on CAVs. So far, researchers have tried to precisely build real-world scenarios in simulation environments.

Limited research has done so far for testing CAV-based traffic signal control algorithms in the real world. One example of this is Zheng et al. (2018) who proposed an integrated platform to estimate traffic volumes by vehicle trajectory data and then optimize traffic signal parameters (such as cycle length, offset, and green times). They tested the methods in the City of Jinan, China by using vehicle trajectory data from Didi, a ridesharing company. The results of two case studies showed that the proposed signal control algorithm could reduce delays by 5–20%. Meanwhile, CV-based or CAV-based testbeds such as M-City (Uhlemann, 2015) and Changshu Testing Ground (Li et al., 2016, 2018a, 2018b) have been increasingly built in recent years. Researchers should seek opportunities to test/validate CAV-based traffic control methods using those testbeds.

Testing and validating various CAV-based control methods and strategies in real-world traffic intersections, corridors, and networks can also help demonstrate the benefits and discover/resolve potential issues of CAV-based traffic control to decision-makers and the public. This is a critical step for transitioning the CAV-related research results and methods from laboratories to the real world to make a real impact. As the CAVs technologies are becoming mature, we hope that at least a few of the CAV-based control methods could soon be tested and validated. The field test results can then help gain valuable insights into CAV-based urban traffic control and select the best-fit control methods for our cities to deploy.

4.5. Implementation requirements of CAVs technologies

The successful applications of the aforementioned traffic control methods rely on proper implementations of both CAVs and the supporting infrastructure.

First, the reliability of V2X communications is one of the critical factors that may influence the performance of CAV-based traffic control. The delayed/missed vehicle information and the position errors (Meng et al., 2018; Shen and Stopher, 2014; Waterson and Box, 2012) may lead to failures of pre-selected signal timing plans or even result in traffic accidents. Generally speaking, actuated traffic control and planning-based traffic control are less vulnerable than platoon-based traffic control and SVCC. However, we believe that robust planning (Yin, 2008) and stochastic programming (Tong et al., 2015) can still be helpful, unless the V2X communications become very robust. Since network traffic control requires transmitting information over a large distance, many researchers believe that 5G communication should be one of the supporting backbones for the communications of the next generation traffic control systems, due to its speed and transmission range. Therefore, 5G-based CAVs communications should be studied and tested for urban traffic signal control.

Second, the cybersecurity issues of CAV technologies (e.g., V2X communications) and traffic control systems should also be carefully investigated. Cybersecurity should address at least two major issues: privacy protection of individual users/vehicles, and the security of vehicles and traffic control systems. Existing research on this topic is rather sparse. Privacy protection is mainly related to the collection and use of CAV data, which has been briefly discussed in Section 2.4. Regarding the security of traffic control systems, in a recent study, Feng et al. (2018) proposed a method to test the vulnerability of actuated and adaptive traffic signal control systems in a CVs environment. Falsified data were sent from four typical elements including signal controllers, vehicle detectors, roadside units, and onboard units to try to maximize the network-wide delay. The experimental results showed that some attacks could significantly increase congestion, while others may even reduce the total delay. Chen et al. (2018) also analyzed the vulnerability of CV-based transportation system by focusing on a realistic attack that aims to create traffic congestion. Compared to the systems without CV-based signal control, the attacks could significantly reduce the mobility of CV-based signal control systems by up to 23.4%. It is expected that with the wide deployment of CAV technologies and the implementation of CAV-based traffic control, the cybersecurity of vehicles and traffic control systems will become increasingly critical. This calls for innovative and comprehensive investigations of this important topic in the near future.

Third, traffic control systems need to be continuously updated to keep the pace with CAVs technologies, since automated vehicles and conventional human-driven vehicles will co-exist for a relatively long time. For example, the computational capability of traffic control systems needs to be improved. Otherwise, we may neither fully utilize the information collected by CAVs to improve traffic efficiency nor respond to the prompt changes of traffic demands.

5. Conclusions

Inspired by the rapid developments and potential benefits of connected and automated vehicles (CAVs), researchers have studied extensively in the last decade on the design and control of future urban traffic intersections. Following this trend, this paper provided a comprehensive review of the methods of CAV-based urban traffic control. The review started with CAV-based deterministic and stochastic traffic states estimation methods, which are essential to traffic control. The review then summarized different types of CAV-based methods for traffic signal control and/or vehicle guidance/control. We further presented a conceptual mathematical framework to formulate the CAV-based urban traffic control. Based on this framework, we discussed the relations and differences among different types of CAV-based traffic control methods by specifying the state variables, control inputs, and environment inputs for each method. Representative results were briefly outlined to illustrate the merits and shortcomings of various traffic state estimation methods and traffic control strategies. Detailed discussions were also provided to present several future research needs and directions in this important area.

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Appendix A. Supplementary material

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