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Review

Urban Traffic Signal Control under Mixed Traffic Flows: Literature Review

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Abstract: Mixed traffic flows are opening up new areas for research and are seen as key drivers in the field of data and services that will make roads safer and more environmentally friendly. Understanding the effects of Connected Vehicles (CVs) and Connected Autonomous Vehicles (CAVs), as one of the vehicle components of mixed traffic flows, will make it easier to avoid traffic congestion and contribute to the creation of innovative applications and solutions. It is notable that the literature related to the analysis of the impact of mixed traffic flows on traffic signal control in urban areas rarely considers mixed traffic flow containing CVs, CAVs, and Human Driven Vehicles (HDVs). Therefore, this paper provides an overview of the relevant research papers covering the topic of urban Traffic Signal Control (TSC) and mixed traffic flows. Best practices for intersection state estimation and TSC in the case of mixed traffic flows in an urban environment are summarized and possible approaches for utilizing CVs and CAVs as mobile sensors and actuators are discussed.

Keywords: mixed traffic flows; connected vehicles; connected autonomous vehicles; traffic signal control; intersection state estimation

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1. Introduction

Due to globalization and the growth of urban areas, there are now more cars on the roads than ever before. As public transportation and cars use the same urban road traffic infrastructure, traffic congestion is the main issue facing almost every city. Urban roads are notorious for their traffic jams, which mostly happen at intersections where conflicting traffic flows are safely managed by traffic signals. In general, urban congestions can be divided into recurrent and non-recurrent. Recurrent congestions are primarily brought on by the physical limitations of infrastructure, daily recurring periods of increased traffic demand, and infrastructure management. Non-recurrent congestions are primarily brought on by traffic accidents, special events (sporting events, concerts, vehicle breakdowns, roadworks, etc.), and traffic incidents [1]. Recurring congestions are simpler to identify, and suitable traffic control measures can be prepared in advance to alleviate them. For the latter, accurate traffic state estimation is essential because identifying congestion is the first step in finding a solution to it. Successful congestion or its build-up detection allows for implementing suitable congestion-relieving measures, such as signal program changes or vehicle rerouting.

Frequent traffic congestions have an impact on daily living and present a variety of difficulties. Reducing traffic congestion minimizes environmental pollution while simultaneously enhancing travel efficiency and safety. Researching causes of congestion, the authors of [2] found that the most statistically significant relationships occurred in the case of the number of business entities and the number of passenger cars implying that congestion is more frequent in areas with a higher number of business entities. Air pollution and fuel loss are side effects that become severe issues as traffic congestion extends the time a vehicle is on the road. According to [3], the combined cost of traffic congestion in

France, Germany, the United Kingdom, and the United States is expected to increase from USD 239.5 billion in 2020 to USD 293.1 billion by 2030. Thus, finding new ways to reduce traffic congestion is important for improving everyday life in urban areas.

Due to the widespread use of numerous Traffic Signal Control (TSC) systems worldwide, TSC is now a key element of Intelligent Transportation Systems (ITS) traffic control services. Many new technologies can be adopted in TSC and especially ITS. Artificial neural networks, fuzzy systems, and evolutionary computation algorithms are the core components of computational intelligence, which provides flexibility, autonomy, and robustness to handle the non-linearity and randomness of traffic systems [4]. Accurate modeling and short-term traffic prediction are quite challenging due to traffic's intricate characteristics, stochastic, and dynamic traffic processes [5]. Due to their randomness and non-linearity, real-world data have limited applicability in short-term traffic state estimation [5,6].

Being able to solve complex real-world problems, in recent years, multi-agent systems also gained significant importance in the field of traffic engineering [7]. As in any domain, solving traffic engineering problems also requires domain expertise. Specially since relying on multi-agent systems, problems can be divided into multiple smaller problems that require less domain expertise. Due to this advantage, it offers in resolving complex problems with uncertainties, multi-agent systems have drawn a lot of attention in the field of TSC. These systems provide a highly flexible and modular structure that incorporates domain expertise to achieve the optimal solution [7].

The emerging mixed traffic flows enable even more control strategies for TSC. Mixed traffic flows are the result of the coexistence of conventional Human-Driven Vehicles and Connected Vehicles (CVs). One has to note that a CV is considered any vehicle, e.g., Connected Autonomous Vehicles (CAVs), and HDVs, being able to communicate with the environment whether that is another vehicle, infrastructure, or pedestrians [8]. Having the possibility to operate as mobile sensors, the appearance of CVs and CAVs has opened up new areas of research regarding ITS. Equipped with Radio Detection and Ranging (RADAR), Light Detection and Ranging (LIDAR), cameras, and many other sensors, CVs have significant advantages compared to conventional fixed-mounted traffic sensors. While conventional sensors cover only specific measurement points, each CV is a mobile data source that can provide real-time spatiotemporal measurement data. Thus, instead of having the traffic information for certain road sections, the data from CVs or CAVs can provide insight into the traffic state along the road on a microscopic level. Moreover, CVs or CAVs have advantages over existing traffic sensor technology because they are not limited by the line of sight like cameras and, as mentioned, collect large amounts of data at the microscopic level, which is convenient for studying traffic. Such large amounts of data will be generated by future mixed traffic flows containing classic vehicles and CVs or CAVs. The share of the latter will rise, decreasing the need for classic traffic sensors (inductive loops, cameras, radars, etc.).

Although CVs can provide data on the microscopic level, those data must be preprocessed before they can be used as input for various TCS systems. Hence, having a lot of data requires data processing to be fast and efficient. Therefore, the question of how to process large quantities of data quickly and efficiently using the potential of CVs and CAVs as mobile sensors and actuators arise. CAV-based multi-agent based traffic control systems are a possible solution as a single agent can process a small piece of information acting on it, and more agents together can handle very complex processes, including a network of intersections [9]. Thus, another question is the applicability of the CVs or CAVs in the multi-agent system since both can also receive information about the traffic state ahead. Based on the received information, CVs or CAVs can also act accordingly, creating a closed-loop control system assuming the driver will use the received information like a CAV would.

The presented topic overview leads us to the motivation for this review paper as similar reviews like [10–12] do not explicitly address the problem of mixed traffic intersection control. Thus, the contributions of this paper are as follows:

- Overview of relevant research papers on the topic of urban TSC and mixed traffic flows with a systematic overview of conventional TSC strategies, and intersection state estimation methods.
- Analyzed the impact of mixed vehicle traffic flows on TSC.
- Suggestions for further research steps on the topic TSC of mixed traffic flows in urban environments.

The rest of the paper is organized as follows. Section 2 describes the research methodology. In Section 3, the technological background is given. Conventional TSC strategies are described in Section 4. Intersection state estimation methods are presented in the following Section 5. Section 6 describes the impact of mixed traffic flows on TSC. The concept of the connected and autonomous vehicle-based TSC is described in Section 7. The discussion with open questions is given in Section 8, and Section 9 concludes the paper.

2. Research Methodology

2.1. Open Questions and Scope Definition

As mentioned, this review paper is focused on the analysis of the impact of mixed traffic flow on TSC in urban areas. Reviewed papers analyze the applicability of CV as data sources for adaptive traffic signal control, as well as the impacts of mixed traffic flow on traffic signal control and urban dynamics. To accomplish the research's objectives, the following research questions were defined:

- RQ1: What are the intersection state estimation approaches?
- RQ2: What is the impact of mixed traffic flows on urban traffic dynamics?
- RQ3: How to process large amounts of data quickly and efficiently using the potential of CVs and CAVs as mobile sensors?

2.2. Applied Research Method

We focused on articles available online and published in English between 2017 and 2021 available in the following digital libraries:

- Scopus;
- IEEE;
- Web of Science (WoS).

We searched for relevant papers using keywords and keyword combinations, considering newer research publications, as well as prominent papers they referenced. A tabular overview of the referenced papers is shown in each section separately. Used keywords were: Mixed traffic flows; Connected Vehicles; Connected Autonomous Vehicles; Traffic Signal Control, and Intersection State Estimation.

3. Technological Background

The rise of CVs and CAVs is attributed to recent advancements in the automotive industry, and CAVs are anticipated to be accessible to the general public in the near future. Along with the deployment of CVs and CAVs, communication systems such as the Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Vehicle-to-Everything (V2X) will be implemented in the transportation environment.

3.1. Intelligent Transportation System Overview

The development of a sustainable transportation system requires efficient use of existing infrastructure and continuous integration of information and communication technologies. Data transmission, traffic flow control, and the administration of transportation networks are all made possible by the deployment and application of cutting-edge communications and electronic and computational capabilities. A large number of these systems were closed systems running independently or in a closed system environment. To deliver better and safer mobility and transition to ITS, these systems have to collaborate and interact with one another [13] as shown in Figure 1. The emphasis of this paper is on Advanced Traffic Management Systems.

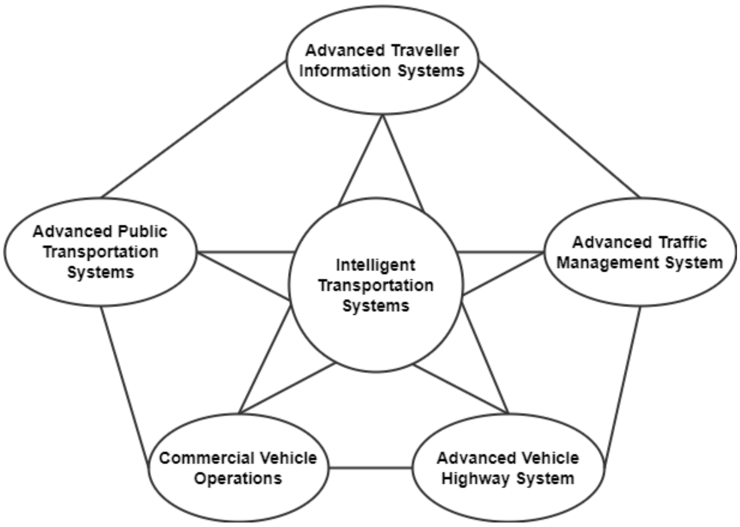

Figure 1. Schematic overview of ITS components [14].

The key factor for the success of ITS is the technology to access, gather, and interpret measurement data collected by various traffic sensors and, among others, from CVs and CAVs related sensors. Generally, two types of sensing platforms can be distinguished in this case: intra-vehicular sensing platforms and urban sensing platforms [15]. As the name suggests, the intra-vehicular sensing platform gathers information about a vehicle's conditions, while urban sensing platforms gather data on traffic conditions. To capture data during V2V and V2I interactions, sensor technology is a crucial component. Based on the collected data, the transportation management system are then given access to these data for additional processing, analysis, and decision-making [15]. Thus, relying on CVs or CAVs eliminates classical problems with traffic data collection. Having the ability to communicate with the environment, CVs or CAVs can provide data beyond the line of sight of fixed-mounted classic sensors. Exploiting that detailed data from CVs or CAVs, the temporal and spatial characteristics of congestion can now be precisely determined. Thus, more effective traffic control and vehicle rerouting countermeasures can be planned and implemented. Computing with those new data sources can provide appropriate solutions, e.g., altering the timing of traffic signal programs, disseminating data via variable message signs and vehicle navigation systems, or even planning new road capacities. Moreover, collected data from CVs or CAVs can also be used for the evaluation of implemented congestion countermeasures [16].

The implementation of ITS solutions based on CVs or CAVs has advantages for every entity in the traffic and transportation ecosystem. It is manifested in the improvement of the overall transport network level of service. The advantages for society include a decrease in traffic accidents by promoting safe driving. Furthermore, traffic congestion decrease can be achieved by proper and timely traffic information distribution, which will also benefit by reducing the environmental impact of traffic. Road maintenance services will benefit from exploring traffic data and detecting unsafe regions and frequently congested places. Furthermore, the drivers will gain benefits in terms of expenses, comfort, and safety.

3.2. Traffic Signal Control Importance

Properly located, operated, and maintained traffic lights may have multiple advantages. Suitably positioned and designed traffic light systems may provide controlled movement of traffic by assigning right-of-way to conflicting traffic flows. Thus, traffic lights can increase the effective capacity of an intersection enabling conflicting traffic flows to share the same infrastructure while controlling traffic flows reduces the possibility of accidents. Traffic signals ensure continuous movement of traffic, especially when traffic control on a particular intersection is coordinated with surrounding intersections. TSC types can be differentiated as coordinated or isolated. Isolated TSC operates independently of traffic signal controllers at surrounding intersections. Contrarily, coordinated traffic signal timing is coordinated with surrounding traffic signal controllers to achieve better throughput [17]. Considering the way the TSC systems operate, they can be classified as fixed-time, fully actuated, and semi-actuated traffic signals [17]. While fixed-time traffic signals operate according to a predefined schedule, fully actuated and semi-actuated traffic signals employ detection of the presence of vehicles or pedestrians to actuate particular phases. The difference between actuated and semi-actuated is that the latter guarantees at least one phase will be served while other phases are actuated. Fully-actuated traffic signal skips a particular phase if a vehicle or pedestrian is not detected. As one of the most efficient ways to reduce traffic congestion at intersections, TSC is a crucial instrument in managing traffic flow [18]. Further study on TSC is still required because of the recent increase in the popularity of CAV technology. When it comes to improving of TSC, adequate mobility data from CVs or CAVs will reflect the dynamics of the city's traffic more precisely and give insight into the city traffic dynamics crucial for further TSC improvement.

3.3. Characteristics of CVs and CAVs

The ever-increasing connectivity around the world has inevitably affected vehicles. Thanks to improvements in connectivity and computing power, CVs and CAVs are becoming the new platform for the development of new applications and services. Equipped with advanced sensing technology, CVs and CAVs generate rich traffic data and affect the human-vehicle dynamic, as well as change the impact of traffic on the environment and the economy [19]. CV technologies have already been used to improve fleet productivity and safety. Although the need for CVs and the technology that supports it has advanced significantly in recent years, there are still difficulties in deploying linked and collaborative vehicle applications before CVs' full potential may be realized. Applications for CVs are developed with an emphasis on solving transportation-related issues. The primary study topics are real-time data capture and management, V2V, and V2I communications for safety [15]. Being a rich data source on the microscopic level, the development of CVs created research potential for various applications, and the CV features also found their applications in intersection control systems. Providing real-time speed, heading, and position is valuable data in traffic control systems, allowing additional enhancements in terms of traffic efficiency and safety.

The Society of Automotive Engineers (SAE) in [20] defined six levels of automation, where level 0 is without any automation, and level 5 implies full autonomy. The first three levels are vehicles equipped with support features for drivers. Level 3 automation means that the driver must take over control of the vehicle when requested. Levels 4 and 5 are capable of autonomous driving without requesting the driver to overtake control [20]. Although CAVs have a higher SAE level of automation, they can be considered as a subgroup of CVs since they employ V2X communication. Since CAVs are equipped with sensors, which can detect adjacent objects and the ability to communicate with other CVs and CAVs, their driving characteristics will be different from those of conventional HDVs.

In contrast to the delay in human reaction time or the negative impacts of human mistakes, CAVs are able to obtain more precise driving-condition characteristics than human perception, enabling them to respond to changes in driving circumstances more quickly. The distance between two successive CAVs is much smaller than that between two conventional HDVs because the CAVs can be driven closely together using Adaptive Cruise Control (ACC) technology [21]. It is important to note that the ACC technology is not reserved for CAVs only; it is present in conventional HDVs too, but without collaboration capability with other vehicles.

4. Conventional Traffic Signal Control Strategies

This section, through three subsections, describes conventional TSC strategies. They serve as the basis for the development of more advanced TSC approaches, including new TSC approaches for mixed traffic flows.

4.1. Signal Program Parameters

Traffic signal parameters define how an intersection can be controlled regarding traffic flow throughput. Depending on the parameter setup, the intersection can operate in various traffic conditions. Each signal program is defined with the following parameters [17,22]:

- Green time: The time duration in seconds, during which a given traffic movement at signalized intersection proceeds at a saturation flow rate.
- Cycle length: The amount of time it takes a signal to complete the signal cycle.
- Phase sequence: The sequence in which the signal program phases occur throughout a signal cycle.
- Change interval: Also known as a Clearance interval, a short time period to provide clearance before the green time for conflicting traffic movements.
- Offset: The relationship in time between the beginning of the signal cycle between two or more consecutive intersections.

4.2. Fixed Time Traffic Signal Control

The Fixed Time Signal Control (FTSC) strategy, also known as open-loop control, relies on historical data. Obtained signal programs have predefined more or less optimal phase sequences based on historical data, which corresponds to daily traffic volume fluctuations. However, when relying on historical data, optimal signal programs mean the plans are optimal only for traffic patterns that are derived from historical data. The traffic patterns tend to change over time, thus, the signal programs will become obsolete or at least suboptimal at some point. Examples of FTSC strategies are Webster's method [23] and its extensions, SIGSET [24], SIGCAP [25] for isolated intersection control together with MAXBAND [26] and its extensions, TRANSYT [27], and MULTIBAND [28] for coordinated intersection control.

Calculation simplicity is the advantage of FTSC, but predefined signal programs can not alleviate occasional events such as traffic accidents, roadworks, special events (e.g., concerts, social events), etc. Furthermore, traffic volume fluctuations differ from day to day, which affects the effectiveness of predefined signal programs since signal programs may not be optimal due to constant fluctuations in traffic volume. To overcome the drawbacks of FTSC strategies, first actuated and then Adaptive Traffic Signal Control (ATSC) strategies were introduced.

4.3. Adaptive Traffic Signal Control

4.3.1. Conventional Adaptive Traffic Signal Control Strategies

ATSC strategies respond to fluctuations in daily traffic patterns by adjusting signal program timing according to current traffic demand, reducing traffic congestion, delays, and travel time [29]. ATSC was first proposed as early as 1960s [30]. Early studies and implementations include SCOOT [31], SCATS [32], UTOPIA [33], and RHODES. SCOOT and SCATS are conventional systems that rely on loop detectors and communication infrastructure to collect traffic data. The main philosophy of these systems is a fast response to the change in traffic demand generating green signal time. They are based on solving an optimization problem during operation. Emphasize of adaptation can be changed by setting the appropriate optimization criteria (intersection throughput maximization, delay minimization, giving priority to public transportation). Recently developed systems such as RHODES can realize also proactive control by predicting traffic demands at a downstream intersection and optimizing lost times on a global scale [34].

4.3.2. New Adaptive Traffic Signal Control Strategies

Recent approaches to creating ATSC are based on machine learning [10]. Machine learning presents the foundation of intelligent traffic signal controllers with the ability to improve in the long term by gaining new knowledge on how to control traffic flows in different situations. The performance of such intelligent traffic signal controllers greatly depends on how they are trained and developed using optimization algorithms [35]. Recent years have seen significant progress in forecasting algorithms as well as the availability of real-time data, which has accelerated the development and applications of machine learning and artificial intelligence in TSC. Proactive models can predict the flow of traffic before it happens and calculate the necessary changes in the TSC system to prevent it completely or reduce the adverse effects [22].

Whether real-time measured or predicted traffic volume values are used, these ATSC systems have their pros and cons. One aspect of their operation is generating a so-called "green wave signal" for large vehicle flow by optimizing the network's traffic signal offset values according to the current traffic demand. Generating a "green wave signal", ATSC strategies can reduce delay and the number of stops and consecutively increase the throughput of intersections. A reduced number of stops reduces fuel consumption, which positively impacts the environment in terms of air and noise pollution. Approximation models of energy consumption and gas emissions have been used as objective functions in traffic signal optimizations, and as a result, using such approximation models may result in an unrealistic traffic signal program configuration [36]. A signal program should be robust such that it is less sensitive to demand variations and can maintain near-optimal performance during varying traffic demand [37].

ATSC systems use both predicted and real-time traffic arrivals to maximize the corresponding objective functions. Such systems also use cameras and inductive loop/magnetic detectors to track vehicles, which has considerable downsides in terms of cost and functionality. Namely, in urban areas, a green wave can be generated only in one-way corridors with ensured communication between intersection controllers. The system's initial implementation costs are around USD 30,000 per junction, or USD 28,800 per mile every year [38]. These systems also require a sizable communication network that can support centralized control with a high data rate. As a result, many towns throughout the world have created systems that are expensive to construct and run. Moreover, there is the risk of experiencing problematic issues with the entire system when the central control computer malfunctions.

In [39], authors designed ATSC for arterial intersections based on Reinforcement Learning (RL). Its advantage is the ability to constantly learn during operation. Depending on the perception of the traffic dynamics, the RL agent dynamically controls offsets and green splits of the arterial intersections. The proposed algorithm is tested in simulation software in 200 random traffic scenarios. Compared to a fixed-time signal scheme with optimization of offset and green-split, results showed a reduction in the number of stops and delays. Such an approach enables improvement during operation. Thus, traffic control at signalized intersections should be based on adaptive approaches, rather than conventional and actuated signals [40].

5. Intersection State Estimation

To implement an ATSC, the current state of the respective isolated intersection or intersection network must be known. The state is related to the intersection level of service, throughput, queue length, (average) vehicle speed, etc. Using the current intersection state value, appropriate changes to the signal program can be made. Thus, urban traffic state estimation is the subject of interest for many researchers. Researchers used different data sources in the literature and explored various traffic state estimation methods. Thus, research papers often can not be strictly categorized since the authors mostly combine various data sources and methods. In general, the developed traffic state estimation methods can be categorized into the following categories: (i) model-driven, (ii) data-driven, and (iii) streaming-data-driven methods [41]. A tabular overview of referenced papers in this section is summarized in Table 1.

Table 1. Tabular overview of referenced papers regarding intersection state estimation.

Paper	Year	Data Source	Type	Applied Method	Impact	Benchmark
[42]	2022	Simulation, FCD	Streaming-data driven method	Bottleneck Probability Estimation Using STM	Bottleneck probability estimated on the simulated motorway traffic scenarios	Evaluated on four different simulated motorway traffic scenarios
[43]	2021	Simulation, FCD	Streaming-data driven method	Intersection state estimation using STM and Fuzzy logic	Intersection Traffic State Estimation using STM	Crossvalidation
[44]	2022	Simulation, FCD	Streaming-data driven method	Statistical analysis	Analysis of impact CVs on STM accuracy	Statistical validation
[45]	2021	GPS, FCD	Data-driven method	Data mining	Estimation of congestion zones and time-varying travel time indexes	Real travel times, historical dataset, and state-of-the-art method
[46]	2021	FCD	Model-driven method	Directed graph	Estimation of vehicle density in every road section	Realistic simulation
[47]	2021	Camera	Streaming-data driven method	CNN	Robust approach for queue length estimation	Comparative analysis to Yolo v3,4,5
[48]	2021	GPS	Data-driven method	Clustering	Congestion identification on global scale	Real data
[49]	2020	Street view imagery	Model-driven method	GCN model	Model based prediction of congestion	Compared to Taxi GPS dataset
[50]	2020	GPS	Data-driven method	Schatten p-norm model for speed-matrix completion	Monitor and visualize traffic dynamics via stochastic congestion maps	kNN, NMF
[51]	2020	GPS	Data-driven method	Classification, STM	Traffic state estimation on citywide scale	Cross-validation
[52]	2019	Camera	Streaming-data driven method	Background difference and AdaBoost classifier	Fast video-based queue length detection	Compared to traditional Adaboost-based method
[53]	2019	GPS	Model-driven	Adaptive multi-kernel support vector machine	Short-term traffic flow prediction	Real data
[54]	2019	GPS	Data-driven method	Classification	Turn-level congestion	Cross-validation with labeled data
[55]	2018	GPS	Data-driven method	Data mining	Method for queue length, level of service and control delay estimation	None
[56]	2018	Sensors, floating car data	Streaming-data driven method	Data fusion	Robust traffic state estimation approach	Realistic simulation
[57]	2017	GPS	Data-driven method	SVM model	Short-term traffic prediction	Historical data-based model, moving average data-based model, ANN model, and k-NN model
[58]	2017	GPS	Data-driven method	Classification	Detecting traffic congestion and incidents from real-time GPS traces	Cross-validation

5.1. Model-Driven Methods

Model-driven methods are based on knowledge of physical traffic flows where applied models represent the physical flow. Models have high explanatory characteristics, which means it is possible to explain the inaccuracy even if the estimation is inaccurate. However, a poorly calibrated model can affect the performance of the estimation method [41].

The authors of [48] modeled the traffic flow network based on taxi's Global Positioning System (GPS) trajectories. The proposed model can reflect the real state of the network, where the nodes represent congested areas and the weight of the edges between nodes represent the congestion coefficient. Scalability is the main benefit of this approach, which is achieved by adjusting the size of the area represented by the node. Although the model was reliable, relying on the GPS traces introduced certain limitations regarding the precision of calculated distances and waiting times.

In [57], a short-term traffic prediction method is proposed based on a novel single-time-step prediction model that simultaneously considers spatial and temporal characteristics of the traffic. The obtained results confirmed the Support Vector Machine-based (SVM) model applicability for short-term traffic speed prediction. The authors of [53] also researched short-term traffic flow prediction. Although their work focused on improving short-term traffic flow predictions, the authors proposed an SVM-based method with an adaptive multi-kernel function and spatio-temporal correlation. The benefit of such an approach is that the SVM has conventional features while using different kernel functions is more suitable for time-varying traffic flow assessments. Conducted experiments imply that this method can adapt to dynamic traffic flow characteristics on urban roads. Obtained results also revealed certain delays between predicted traffic flow compared to the real values used for comparison.

The authors of [49] proposed a Graph Convolutional Network (GCN) model for evaluating the potential of estimating congestion areas. This method relies on road street-view imagery and Point of Interest datasets, which are used as input for the GCN to detect urban areas with a high probability of congestion. The proposed method reveals the potential of exploiting open data to solve conventional challenges in urban traffic and applying this method in different cities could give different results. To evaluate the method, the authors used ground truth data derived from GPS data collected by taxi vehicles, and GPS data have their limitations, as mentioned earlier.

5.2. Data-Driven Methods

The GPS is commonly used as a data source for data-driven methods. Required traffic data are mostly collected by GPS-equipped taxis or delivery vehicles. Since GPS cannot always provide accurate data, it is mostly used to determine conditions on the road level using additional preprocessing. Thus, speed profiles for very large road networks can be estimated and used in vehicle route optimization and traffic control [45]. In [54], turn-level congestion is detected by analyzing features of GPS data. By using clustering, the proposed method identifies spatial and temporal characteristics of congestion at the turn level, which is the main contribution of this paper.

In [50], the authors developed an urban network-wide traffic state estimation method capable of processing high-resolution GPS data. The proposed method divides the observed area into cells with corresponding road segments and GPS records. Although the method performs well and can differentiate road segments when the cell is located at the intersection, the algorithm estimation accuracy is reduced in case of data loss during longer time periods. The approach described in [58] also uses GPS data to detect traffic states. The proposed method differentiates three traffic states: incident, slowed traffic and blocked traffic. Traffic states are detected based on vehicle speeds extracted from GPS data and are classified relative to speed thresholds. While this method does not require a learning process, the chosen speed thresholds can affect its performance. Tišljarić in [55] provides another illustration of how aggregated GPS data can be used to determine the queue length and the level of service at an intersection. These techniques rely on GPS data components, such as vehicle speed and position, which rely on the quantity of tracked cars and reliable GPS data samples. As it takes some time to gather adequate GPS data and process them, it is also crucial to consider the time delay brought on by data processing.

Relying on GPS data, the authors of [51] proposed a method for traffic state estimation in an urban area on a city-wide scale. The proposed method represents data in the form of a Speed Transition Matrix (STM), where the transition is defined as a spatial change in vehicle trajectory when traveling between two consecutive road segments. The speeds that the vehicles had on the transition are calculated as harmonic mean speed, and it is written to the corresponding cell in the STM. After creating STMs, traffic state estimation is carried out based on the recorded data's center of mass characteristic. Obtained results indicated that the proposed method is suitable for traffic state estimation.

Data-driven traffic state estimation methods rely on historical data, using statistical methods and machine learning techniques to determine real-time traffic states based on features found in historical data. Dependence on historical data has its drawbacks. Thus, such methods are prone to failure if an irregular event occurs or traffic trends change in the long term, especially in the case without having these two cases in the historical data [41]. Furthermore, low penetration of GPS-equipped vehicles leads to inaccuracy because of a lack of data. Additionally, this estimation method can also benefit from real-time traffic data sources directly into the estimation model, creating the foundation for the third approach described in continuation.

5.3. Streaming Data-Driven Methods

In contrast to previously mentioned methods, streaming-data-driven methods do not require historical data, which makes them robust to unpredictable events. They rely on streaming data and weak assumptions without capabilities for future prediction. For accurate estimation, these methods require large amounts of (real-time) streaming data [41].

The mentioned STM-based method combined with Fuzzy-based systems used for intersection traffic state estimation is also applied in [43]. The road network is divided into segments of equal lengths, and CV speeds were collected to create STMs for each transition. Each STM is normalized as the input for the proposed fuzzy logic-based decision system. Based on the center of mass characteristic and applied set of IF-THEN rules, the fuzzy logic gives as output the bottleneck probability ranging from 0 to 1. The method is tested using a simulated environment containing an isolated intersection. Obtained results revealed the congestion's spatial and temporal characteristics, indicating that this method can be used for intersection traffic state estimation.

Another application of STMs is described in [42] where it is used for bottleneck probability estimation on motorways. The proposed method computes vehicle speeds on consecutive motorway segments, and speeds are represented with STMs. Evaluation of the proposed method on different scenarios resulted in total accuracy of 92%, which indicates possible application on motorways with high CV penetration rates where CVs are used as mobile sensors. Thus, in [44] various CV penetration rates were tested to analyze STM accuracy. The results indicated that STM accuracy decreases during morning and afternoon rush hours. Furthermore, results also indicated that adding new CVs has much more impact on penetration rates up to 30% compared to penetration rates above 30%.

To estimate the queue tail location, the approach defined in [56] fuses traffic detector data with the location and speed of the CVs in a mixed traffic flow containing conventional HDVs and CVs. To compensate lack of data at low penetration rates, the authors developed a probability-based approach making the proposed method robust to varying penetration rates of CVs. The results showed that the proposed method requires only one spot detector upstream of the link. In [46], the authors also relied on data fusion from different sources. The proposed method for traffic state estimation on urban networks utilizes data from three data sources: stationary flow sensors, turning ratios, and floating car data. The benefit of the proposed method is that it requires only turning ratios as an input, thus, road outflows modeling is avoided. This benefit can also be the main drawback since the method relies on turning ratios estimated from stationary flow sensors.

Streaming data-driven methods also include methods based on the data obtained from various sensors for collecting motion information, such as transport video detectors, microwave radars, infrared sensors, ultrasonic sensors, passive acoustic sensors, and others [59]. The authors of [47] developed a video-based vehicle queue length estimation method. The proposed method detects vehicles as objects, and queue length is calculated as the number of detected objects multiplied by the average vehicle length. Similarly, in [52], the authors proposed a real-time video-based vehicle counting method for urban roads. The proposed vehicle counting method is used for each lane depending on the traffic congestion degree determined by the foreground area ratio. A quick area-based method for calculating the number of vehicles is used when the traffic is deemed to be congested. Otherwise, an approach that uses background difference and an Adaboost classifier to recognize and count vehicles quickly is used. The proposed video-based methods were robust to heavy traffic with accurate vehicle counts compared to ground truth data. Both methods have common drawbacks—the video quality can be affected by environmental changes (weather, lightning, etc.), and the estimation error increases as traffic volumes increase.

6. Impact of Mixed Traffic Flows on Traffic Signal Control

The introduction of CVs alters traffic flow dynamics, increasing the effective road capacity as the penetration rate of CVs rises. Driven by advanced sensing and computing capabilities, and by utilizing V2X communication CVs can percept the environment. They also share onboard data (speed, position, and heading) in real-time with the environment through V2X communication. Thanks to sensing technology and real-time communication, vehicles are becoming also a good basis for developing new ITS-related applications and services. Exchanging traffic information CVs will have timely information about the traffic state and can recommend the driver's ideal vehicle speed or alternative route. Relying on computation capabilities, CAVs will be part of a multi-agent system, where each vehicle will make decisions based on available data, which means CVs will affect traffic flow characteristics, increasing throughput and reducing delays. CVs are the vehicles with more information and recommendations, while CAVs are the vehicles with more information and orders. It is important to emphasize drivers' compliance in CVs as they receive recommendations from the TSC contrary to CAVs that receive the orders.

To enhance the performance of CV applications at low penetration rates, the authors of [60] proposed a new method to estimate the speeds and positions of CVs and non-connected vehicles. The proposed method utilizes the information collected from CVs and the speeds and flows of conventional vehicles collected from loop detectors. Thus, the proposed method estimates the forward movement of conventional vehicles based on collected data from CVs and sensors. Obtained results showed that estimation error increases as the CVs penetration rate decreases. Furthermore, estimation error decreases as the traffic demand decreases. For CVs penetration rates above 20%, the CVs-based TSC strategy outperformed the commercial EPICS adaptive control in terms of minimizing travel time delay and the number of stops. EPICS is an adaptive control system for individual intersection optimization developed by PTV Group. It calculates signal program parameters every second based on real-time traffic conditions, and depending on current conditions system decides whether the phase needs to be adjusted [61]. Results presented in [62] also indicated that the penetration rate of CVs above 20% improves traffic operations compared to existing approaches. The authors developed algorithms for mixed flow traffic state estimation, where the mixed traffic flow is contained of CVs and conventional vehicles without communication capabilities (both types of vehicles are HDVs). The CVs and sensors provided information about traffic, and the proposed methodology adjusted signal timing accordingly. Testing in a simulated environment on five scenarios indicated that even at the 10% penetration rate of CVs, the number of completed trips increased by 3.2%.

From the above mentioned facts, it can be observed that the penetration ratio of CVs affects the traffic flow dynamics, although the CVs only provide onboard data. Being able to operate independently of the driver suggests that the CAVs could be used as the actuators in mixed traffic flows executing orders obtained from the TSC. Results from [21] indicated that the increase in road capacity happens gradually before the penetration rate of CAVs reaches 30%. Road capacity growth rate is mainly determined by the CAV capability on the desired time gap when the CAV penetration rate is over 30%. The traffic system performance improves as the percentage of CVs and CAVs increases. Thus, because their current market penetration rate is low, improving TSC is still challenging for traffic engineers to open new research/application areas.

The use of CVs and CAVs is expected to have advantages such as increased road capacity, traffic safety, and efficiency. As mentioned above, acting as mobile sensors, CVs will provide rich real-time information to the TSC system. Based on provided data TSC system have better insight into the traffic state, and gathered information is used for optimizations of signal programs. Therefore, the TSC system can also inform drivers about the current traffic state, recommending the driver's optimal speed profile and/or route. Currently, it is up to the driver if he will follow the recommendations. CAVs are also mobile sensors but provide even more information to TSC systems since CAVs are usually equipped with more sensors than CVs. Moreover, CAVs can be controlled by the TSC system, where the TSC system informs CAVs about signal phase timing and sequence. With such information, a particular CAV can alter its speed and route to reduce travel time and emissions. With a sufficient penetration rate, CAVs can affect the speed of other vehicles in traffic flow. However, a heterogeneous traffic flow made up of conventional HDVs, CVs, and CAVs will exist for a while before the CAVs are fully deployed, which could cause uncertainty in the existing transportation system. How much and in which way will the existing transportation system be affected is currently unknown. Furthermore, it is necessary to assess the connection between CVs and CAVs penetration rates and potential improvements in road capacity. A tabular overview of referenced papers regarding the impact of mixed traffic flows on TSC is summarized in the Table 2.

Table 2. Tabular overview of referenced papers regarding the impact of mixed traffic flows on TSC.

Paper	Year	Data Source	Type	Applied Method	Impact	Benchmark
[60]	2019	CVs, loop detectors	Model-driven method	Gipps' car-following model-based CV signal control	Estimation vehicle position and speed	Intersection capacity utilization, EPICS
[62]	2020	Simulation, CV	Data-driven method	TSE algorithms for partially connected networks	Better overall performance compared to existing signal plan	Real-world Vissim simulation
[21]	2018	Simulation	Model-driven method	Two-lane cellular automation	Road capacity growth rate is determined by CAV characteristics	Validation against real-world dataset

7. Connected and Autonomous Vehicles Based Traffic Signal Control

Traffic signals and vehicles are mutually dependent. Increased traffic demand needs different signal programs than decreased traffic demand to ensure maximum intersection throughput. Conventionally, research on TSC did not consider the characteristics of the traffic flow on the microscopic level (information about individual vehicles and their priorities). In reality, signal timing influences the movements of individual vehicles and, thus, their performances (such as emissions and fuel consumption). The most significant contribution to reducing Greenhouse Gas (GHG) emissions have eco-driving and platooning, while faster travel significantly contributes to the increase of GHG emissions [63]. Individual vehicle performances are the critical input to traffic control methods on how to adjust signal timing best [64]. The TSC system relies on the following control parameters when changing the signal program: green time, offset, change interval, and cycle length. TSC system balances these parameters among multiple intersections to reduce delays and the number of stops regarding the controlled small intersection network.

Regarding current research, CAV-based TSC methods are usually designed first for isolated intersections, then extended to corridors and even intersection networks. However, the method extension is followed with the modification of the objective function to consider the coordination of all the intersections [64]. Common approaches to solving TSC problems are centralized and decentralized approaches and are applied in the case of mixed traffic flows also. Centralized approaches usually compress optimization problems of multiple constraints to a single objective problem (e.g., the objective is to increase intersection throughput). Decentralized approaches assume that the neighboring intersections' traffic information is known as environmental input. Although distributed approaches can reduce computation complexity, those approaches may produce only locally optimal results.

Good examples of centralized approaches are [65,66]. In [65], the authors proposed adaptive coordination in the CV environment, which relies on data gathered from CV on-board units. Adaptive coordination incorporates dynamic programming and Mixed-integer Linear Programming (MILP). The proposed methodology uses Dynamic Programming (DP) to reduce vehicle delay at the intersection level for coordinated and uncoordinated phases. MILP is used to optimize offsets along the corridor. Although the method utilizes real-time data from CVs, in the case of CVs low penetration rate, the lack of data is compensated with the data from stop bar traffic detectors. Thus, on average flow data, corridor-level optimization was conducted offline to determine optimal cycle length. Similarly, in [66] the authors developed a signal timing optimization and coordination framework based on mixed-integer nonlinear programming. Problem complexity is reduced by decomposing the problem into two levels: intersection level, where DP is used to optimize phase duration, and corridor level, where the offsets of all intersection signal programs are optimized. The method was tested in a simulation environment under various scenarios, and obtained results revealed that the proposed method outperformed traditional actuated signal timing and coordination plan. Furthermore, while the signal coordination scheme was favorable for corridors with high traffic volumes, signal coordination had limited benefits for intersections with low traffic volumes. Distributed-Coordinated methodology for signal timing optimization in connected urban street networks is proposed in [67]. With the underlying assumption that all vehicles and intersections are connected and can share information, the network is decomposed into multiple individual intersections. For each intersection, a MILP needs to be solved. Such an approach is a real-time and scalable solution technique for signal timing optimization, where the timing decisions are made at the intersection level. Another distributed approach example is proposed in [68], where the authors used a back-pressure-based signal optimization method, combining fixed phase sequences with spatial model predictive control. Each intersection is controlled independently, while traffic queue lengths from surrounding intersections are used as input data. The main idea is to balance queue lengths among the intersections, thus, the traffic volume is evenly distributed over the traffic network. The results showed that even the distribution of queue lengths reduces travel time and increases network throughput. In [69], the authors based their research on the possibility of applying imaginary waiting queues and the back-pressure optimization method for intersection management. Imaginary queues are calculated periodically based on the traffic sensors' data that the intersection management system receives. The signal program for the traffic light is determined based on the calculated imaginary queues. The key difference is that the proposed method determines the phase schedule and duration based on historical data.

Tabular overview of referenced researches in this section is summarized in Table 3. The above researches portray the application possibilities of CVs and CAVs in the area of TSC. The computing and communication capabilities of CAVs allow them to be decision-making agents in a multi-agent system. In this context, decision-making means that the CAVs cooperating with other CAVs in real-time can replace conventional TSC, making intersections autonomous. Implementation of autonomous intersections is enabled by infrastructure through V2X communication and CAVs decision-making possibility. Autonomous intersections are a complex topic that requires a lot of components in terms of communication, infrastructure, and security. A possible approach for the autonomous intersection implementation is vehicle platooning, where the vehicles are grouped, maintaining speed and distance. Platoons are coordinated with a leading vehicle, which negotiates the right of way on behalf of the following vehicles [70]. In [71], the authors researched platooning and proposed a scenario of a four-way autonomous intersection in a simulated environment. Applying the Platoon-based Delay Minimization function, results indicated that the average delay is reduced up to 40%. This research considered the ideal situation with CAVs and autonomous intersections. However, considering humans' imperfections, the question arises of how such a system would work with the HDVs. Research results indicated that the average delay increases for all vehicles if there is more than 5–10% of HDVs, where the CAVs were blocked by HDVs [72]. Nevertheless, CVs and CAVs can contribute to alleviating congestion on isolated intersections and corridor intersection configurations with their improved driving characteristics. Namely, CVs and CAVs have a better responses to traffic control signals due to faster reactions to signal change, shorter space and time headways, platooning, and data sharing as described in [70,71].

Table 3. Tabular overview of referenced papers regarding CV and CAV based TSC.

Paper	Year	Data Source	Type	Applied Method	Impact	Benchmark
[66]	2020	Simulation, real-world data	Model-driven method	Traffic signal coordination formulated as MINLP	Improved traffic signal performance	Compared to existing actuated signal timing
[69]	2018	Real-world data	Model-driven method	Back-pressure based ATSC	Reduced average vehicle travelling time	Fixed-cycle and Backpressure algorithms
[67]	2017	Simulation	Model-driven method	Distributed-coordinated methodology for signal timing optimization	The algorithm controlled queue length, maximized intersection throughput and reduced travel time	Tested on different scenarios in simulation
[65]	2017	Real-world data	Model-driven method	Two-level coordination algorithm	Offset optimization along corridor	Actuated-coordinated signal control by Vissim
[71]	2017	Simulation	Data-driven method	Platoon-based intersection scheduling algorithm	Reduce average delay per vehicle by up to 50%	Evaluation in simulated environment

8. Discussion

From the reviewed papers can be concluded that TSC is a topic that produces high research interest in the field of traffic engineering. Although TSC is a well-founded research topic, TSC is still a focus of interest for many researchers applying new findings from optimization, control and machine learning, and with the emergence of CVs and CAVs the field of TSC gained new application possibilities because of CVs and CAVs communication/data sharing capabilities. Regarding the applicability of CVs and CAVs in TSC, questions such as the influence of the penetration rates, data sampling rates, and data processing methodologies can be singled out. In [21], it is stated that CAVs can increase road capacity because of their capability to obtain more precise driving condition parameters compared to HDVs. The authors observed that the increase of the road capacity happens gradually before the CAVs penetration rate reaches 30% penetration rate, and above 30% penetration rate the increase of road capacity depends on CAV capability to maintain the minimum time gap. A similar observation is noticed in research [60–62]. Although the authors conducted the research independently on different models, they observed that a CV penetration rate of 20% improves system performance.

Considering the CV's capability to share onboard data, data-driven methods and streaming-data-driven methods are reasonable choices for real-time traffic control applications even with their pros and cons. While data-driven methods can provide information about conditions on turn-level [54] or even on network level [45], they rely on historical data which means they are prone to failure if an irregular event occurs (e.g., traffic accident). However, streaming-data-driven methods are relying on streaming data and weak assumptions which require large amounts of data. They are more robust to unexpected events and include data from various sensors [41,59].

Driven by the results of the STM applications in [42], it is evident that STMs are one approach for processing real-time data from CVs and CAVs. Thus, future work will be focused on TSC systems for mixed traffic flows, especially the exploration of CV applications in TSC, with the final goal of developing STM-based TSC. The idea of the development will be how to apply the STM to estimate the state of the intersection with the final goal to achieve ATSC, meaning that the obtained information about the state of the intersection will be used as input for the TSC. In the early stage, the goal is to implement the methodology for an isolated intersection and then to upgrade the methodology to more (2 to 4) consecutive intersections or, hopefully, a small network of intersections. To achieve these research goals, it is mandatory to make further research on CV penetration rates and data sampling rates. Results in [44] indicated that STM accuracy varies depending on CV penetration rate where accuracy was decreased during morning and afternoon rush hour, and that is the result of vehicles being stationary. If vehicles are stationary there is a reduced chance of making transitions and STM lacks data. That problem can be alleviated by increasing the number of transitions, however, an increased number of transitions increases the number of generated STMs. The number of transitions and data sampling rate can be determined by performing a sensitivity analysis while the problem of stationary vehicles could be resolved utilizing pattern recognition and machine learning techniques.

9. Conclusions

This paper provides an overview of the current research area state of mixed traffic flows and TSC to alleviate traffic congestion. Causing additional expenses and reducing the quality of life, urban congestion is one of the major problems for every city. Moreover, congestion even affects the development and economic growth of the cities.

The available traffic data sources limit current TSC solutions. Conventional data sources cover only a section of the road in a fixed location, meaning they can provide limited information about vehicles and traffic flows. The rising popularity of CVs changes the traffic characteristics of urban areas. Many researchers explored topics of CV applications in TSC, and most of the results imply that the presence of CVs increases road capacity. Researches imply that the impact of CVs significantly depends on CVs penetration rates. CVs also affect traffic flow dynamics due to their different driving characteristics, and the results vary depending on road type. Thus, the necessary penetration rate of CVs to achieve reliable results remains an open question.

New TSC strategies are complex and require high-resolution data, which CVs can provide. In that context, the availability of real-time traffic data on the microscopic level originating from CVs opens new research possibilities and enables new traffic and infrastructure management solutions. The problem of real-time processing of such data is evident and streaming data methods are a possible solution for this. One promising approach is based on STMs with the possibility of covering urban motorway and intersections traffic scenarios, especially since bottleneck locations and their intensity can be estimated with STMs. Nevertheless, more in-depth insight into the traffic network state can be gathered enabling the development of new TSC approaches using this microscopic-level data. New solutions also apply to TSC, where signal programs can have an effect on a city's traffic flow dynamics.

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Abbreviations

The following abbreviations are used in this manuscript:

ACC	Adaptive Cruise Control
ANN	Artificial Neural Network
ATSC	Adaptive Traffic Signal Control
CAVs	Connected Autonomous Vehicles
CNN	Convolutional Neural Network
CVs	Connected Vehicles
DP	Dynamic Programming
FTSC	Fixed Time Signal Control
GCN	Graph Convolutional Network
GPS	Global Positioning System
HDV	Human Driven Vehicle
ITS	Intelligent Transportation Systems
kNN	k-Nearest Neighbors
LIDAR	Light Detection and Ranging
MILP	Mixed-integer Linear Programming
NMF	Non-negative Matrix Factorization
RADAR	Radio Detection and Ranging
RL	Reinforcement Learning
SAE	Society of Automotive Engineers
STM	Speed Transition Matrix
SVM	Support Vector Machine
TSC	Traffic Signal Control
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-everything

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