



# A Review of Research on Optimisation Methods for Vehicle-Road Cooperative Control

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Review

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## ABSTRACT

Effective traffic control can alleviate congestion, enhance mobility, reduce fuel consumption and improve road safety. In the current environment, the development of vehicle-road cooperative control is a key link in enhancing the high efficiency, economic, digital and intelligent development of urban traffic. This paper systematically reviews key optimisation methods in vehicle-road cooperative control, covering research advances in right-of-way allocation, vehicle speed trajectory optimisation, traffic signal optimisation and co-optimisation of traffic signals and vehicle speeds. It synthesises representative research in these four areas, encompassing related algorithm models and evaluation indicators. Through a comparative analysis of various methods and their evaluation frameworks, the applicability of these methods in enhancing traffic efficiency is tested. Findings show that while existing studies have achieved promising results, most focus on isolated intersections, oversimplifying real-world road networks. Efficient co-optimisation of traffic signals and vehicle speeds for connected and automated vehicles (CAVs) requires moving beyond single-node optimisation to real-world network applications. Finally, the future research directions and challenges are discussed. Hopefully, this review could provide researchers with a helpful roadmap for future research on urban traffic control optimisation methodologies.

## KEYWORDS

urban traffic; vehicle-road cooperative control; vehicle speed trajectory optimisation; traffic signal optimisation; co-optimisation of traffic signals and vehicle speeds.

## 1. INTRODUCTION

Vehicle-road cooperative control technology represents a pivotal advancement in the field of intelligent transportation, marking an inevitable trend in modern traffic management. Numerous countries have initiated dedicated research programs to explore this technology, including the United States' IntelliDrive, the European Union's COOPERS, Japan's SmartWay and China's I-VICS under the 863 Program [1]. These systems facilitate intelligent cooperative control by enabling dynamic information exchange among road users, vehicles and infrastructure, thereby optimising traffic efficiency and safety. Beyond traditional traffic signal control, vehicle-road cooperative systems offer comprehensive functionality [2]. They can provide real-time speed guidance for vehicles based on traffic light timing, dynamically adjust signal timing in response to vehicle trajectories and speeds, and enable coordinated signal control across multiple intersections. This paradigm shift has fundamentally transformed traffic management from a passive, signal-driven approach to a proactive, cooperative framework [3]. Recent research efforts in intelligent transportation are evidenced by global publication data from the Web of Science (*Figure 1*). Over the past five years, China has emerged as the leading contributor with over 2,200 publications, followed closely by the United States with more than 1,300.

Currently, optimisation strategies in vehicle-road cooperative control primarily emphasise four key areas: priority control for vehicle right-of-way, vehicle speed trajectory optimisation, traffic signal optimisation and co-optimisation of traffic signals and vehicle speeds [4]. At present, intelligent transportation systems are undergoing rapid development worldwide, with a proliferation of research findings. However, existing literature provides relatively few systematic reviews of multi-objective collaborative optimisation approaches. This paper comprehensively examines research progress in key areas such as right-of-way allocation, vehicle speed trajectory optimisation, traffic signal optimisation and co-optimisation of traffic signals and vehicle speeds. Through a systematic review of relevant literature, this study aims to provide a valuable perspective for future research.

The remainder of this paper is organised as follows. Section 2 reviews the development of vehicle right-of-way priority control strategies, with a focused summary of bus priority control strategies. Sections 3 to 5 summarise typical research on vehicle speed optimisation, traffic signal control optimisation, and the cooperative optimisation of traffic signals and vehicle speed, along with their corresponding algorithms/models, and optimisation indicators. Section 6 discusses future research directions and challenges in optimising vehicle-road cooperative control strategies, particularly in mixed traffic environments where ICVs coexist with human-driven vehicles (HDVs), considering the continuous advancement and growing emphasis on vehicle-road cooperative control technology. Finally, the paper concludes with closing remarks.

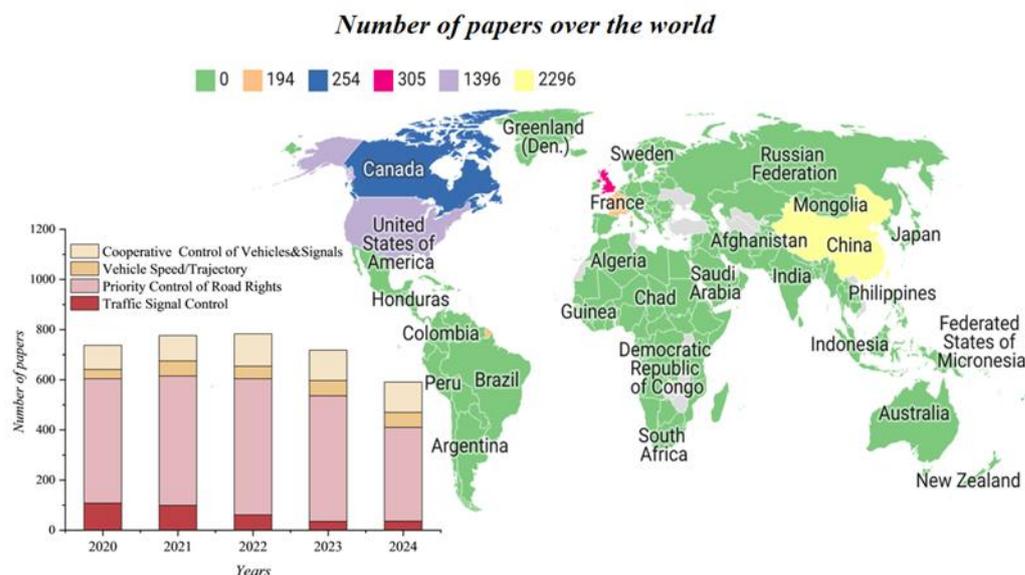


Figure 1 – Summarisation of papers on cooperative vehicle-road control

## 2. VEHICLE RIGHT-OF-WAY PRIORITY CONTROL

From a traditional perspective, the special-vehicle right-of-way priority control method involves providing dedicated lanes [5]. Through lane designation, only buses are permitted in urban public transport lanes, thus reducing the interference of other vehicles and improving their operating speed and punctuality. However, bus-only lanes may result in underutilisation of road capacity during specific periods, while their construction and maintenance require certain investment costs [6].

In the vehicle-road cooperative system, signal priority control is realised based on real-time communication between vehicles and road infrastructure [7-9]. The underlying principle is: when special vehicles or vehicles with priority needs approach the intersection, the vehicle-mounted equipment sends a request signal to the roadside facilities, and the roadside equipment transmits it to the traffic signal control centre. The centre evaluates the request based on vehicle type, location, direction and real-time traffic conditions. If the request is granted, the system adjusts signal timing by extending green lights or advancing green phases in the direction of priority vehicles, ensuring quick and safe passage. Concurrently, vehicles in other directions receive prompt warning information to decelerate or stop in advance. This significantly improves priority vehicle efficiency and facilitates timely emergency response and public services. Current bus priority strategies fall into three categories: right-of-way time priority, right-of-way spatial priority and roadway priority. Right-of-way time priority [10-13] strategy is primarily implemented through traffic signal control, including extending the

current green phase upon detecting an approaching bus or early termination of conflicting red phases to grant prioritised passage rights. Right-of-way spatial priority [14-18] is mainly controlled on intersection entrance roads and involves the use of variable message signs to guide vehicle movement, the use of variable guidance to clear lanes and the use of vehicular-roadway collaboration technologies to guide vehicle operations. Roadway priority [19-21] control strategy primarily targets specific road sections or high-demand routes, enabling green-wave transit for buses at consecutive intersections. Numerous scholars have approached this issue from different perspectives, aiming to develop priority strategies for buses. *Table 1* summarises typical studies on vehicle right-of-way priority control.

*Table 1 – Typical studies on vehicle right-of-way priority control*

Priority control	References	Publication year	Control methodology	To be improved
Right-of-way time priority	[10]	2010	It deployed signal priority strategies for buses, coordinated with other signal processing.	This traffic signal priority strategy is limited to public transport in small and medium-sized areas.
	[11]	2019	It proposed a basic signalling hierarchy model, which further considers the impact of bus passenger demand distribution on dwell times.	The model focuses only on the through movement along the trunk line.
	[12]	2016	A novel bus operation strategy, including holding control and speed control, was proposed.	The model is limited to a single intersection.
	[13]	2019	A model for advanced bus signal priority control was proposed.	The model only optimises the parameters of a typical traffic signal priority strategy.
Right-of-way spatial priority	[14]	2018	An optimisation model was established with the objective of minimising average delay, while simultaneously optimising lane allocation and signal timing.	The model is only a static model.
	[15]	2024	It adopted a hybrid approach that integrated data-driven analysis with simulation, conducting comprehensive quantitative analyses of both conventional lanes and dedicated bus lanes.	Research has focused on conventional fuel-powered buses.
Right-of-way spatial priority	[16]	2023	A real-time dynamic reversible lane safety control model was proposed.	Models need to be further optimised and refined for different driving environments.
	[17]	2021	A system-optimal dynamic traffic assignment problem based on dedicated vehicle lanes was proposed.	It is only applicable to morning commuting networks and emergency evacuation networks.
	[18]	2023	A modelling method for dynamic optimal setting and associated control of intermittent bus lanes was proposed.	Failure to consider the impact of bus patronage and bus stop dwell times at different times of the day on lane settings.
Roadway priority	[19]	2018	It achieved intermittent and dynamic priority by granting intermittent access to dedicated bus lanes, allowing general traffic to utilise the lanes when no buses were present, thereby improving road utilisation efficiency.	No specific controls are provided.
	[20]	2023	The proposed method for dynamic priority control of emergency vehicles based on a cooperative vehicle-infrastructure system.	The model does not quantitatively take into account the relationship between vehicle speed and following distance.
	[21]	2023	Exploring a new approach – lane multiplexing to mitigate conflicts between intersection lane utilisation and transit priority.	This method significantly affects regular traffic.

Although significant progress has been made in optimising bus lanes and prioritising traffic signals, there are still many major challenges. The current method mainly relies on static idealised travel demand models, which cannot effectively adapt to the dynamic and unpredictable characteristics of real traffic, resulting in a lack of flexibility in scheduling schemes and low signal control efficiency. A critical obstacle is the mismatch between older infrastructure and modern vehicle communication technologies, forcing manual intervention for nearly one-third of priority requests and hampering real-time speed optimisation [22]. Additionally, sparse deployment of roadside sensors, especially in constrained urban areas, creates data gaps that further weaken system reliability. Another critical issue is the narrow focus of existing priority systems, which prioritise bus delays at the expense of broader traffic flow. Poorly implemented signal strategies have been shown to increase congestion in non-priority lanes by over 40%, merely shifting rather than resolving bottlenecks. Researchers are now working towards more balanced, multi-objective solutions that dynamically optimise speeds not just for buses, but for all vehicles, to achieve true network-wide efficiency.

### 3. VEHICLE SPEED TRAJECTORY OPTIMISATION

Traditional speed guidance strategies mainly include setting fixed speed limit signs, using road markings and traffic signal guidance. These strategies have ensured road traffic safety to a certain extent, but they also have their own limitations. With the investment in the research and development of vehicle-to-infrastructure (V2I) communication technologies, the stability, reliability and communication speed are improved to ensure enabling efficient data exchange between vehicles and roadside infrastructure. In the early days, real-time intelligent vehicle and road information was used to improve the efficiency of traffic system operations and guide vehicle speed. Early research on the speed advisory system is aimed at improving driving safety. Servin et al. [23] found that using the latest intelligent transport technologies, by applying speed management procedures (often referred to as intelligent speed adaptation), could provide speed guidance while simultaneously reducing fuel consumption and emissions.

At this point, scholars begin to study the adjustment of vehicle driving strategies based on signal light phase time information and vehicle fuel economy to reduce fuel consumption; on the other hand, they explored the optimisation of traffic signal control strategies to balance traffic efficiency and fuel economy [24]. Schwarzkopf and Leipnik [25] may have been the first to develop an optimal control model for vehicle throttle settings, deriving their algorithm from Pontryagin's maximum principle to minimise fuel consumption across varying terrain conditions. Sun C. et al. [26] proposed a surrogate model for the instantaneous optimal energy consumption of the powertrain, engineered using a regression learner to decouple the co-optimisation problem. Comparative validation demonstrates that the proposed adaptive co-optimisation method achieves 14.81% improvement in driving safety while maintaining high energy efficiency. Jiménez et al. [27] developed a speed advisory system, which employs a dynamic programming (DP) optimisation algorithm to analyse real-time traffic conditions and derive the optimal speed profile. Subsequently, a cost function was used to evaluate speed transitions, providing drivers with recommended speed adjustments. He XZ. et al. [28] proposed a multi-stage optimal speed control method that explicitly accounts for vehicle queuing dynamics and traffic signal constraints at intersections, enabling the simulation of fuel-optimised speed trajectories on signalised arterials. Unlike traditional analytical models, their framework incorporates proximal traffic interactions, a critical factor historically overlooked, to achieve minimised vehicular fuel consumption. Zhang et al. [29] proposed a vehicle queue length estimation method, in which the developed sealing layer green light optimal speed advisory system provided recommended optimal speeds. The results showed that this vehicle speed guidance strategy was more energy-efficient than the traditional vehicle speed guidance strategy under undersaturated traffic flow conditions. Chuan M. et al. [30] proposed a method to optimise vehicle trajectory to reduce energy consumption. The inverse dynamics model was used for driving torque and steering control, and the vehicle trajectory was optimised to save energy consumption.

In order to adapt to the development of the times, people are gradually paying more and more attention to the development of autonomous driving systems and electric vehicles [31]. This means that improving energy efficiency and ensuring precise speed are crucial for improving the performance and sustainability of autonomous vehicles. Combining optimisation methods with intelligent systems is one way to solve complex problems in autonomous vehicle operation and design. Smart algorithms and machine learning capabilities can be used to provide autonomous vehicles with the intelligence to dynamically modify their energy consumption and speed profiles in real time to optimise efficiency while maintaining safety and performance standards [32]. Manavaalan et al. [33] developed a system that integrated hybrid electric vehicles with autonomous vehicle

technology, in which enhanced manta ray foraging optimisation technology was used to significantly improve speed control and energy economy. The analysis of the results showed that significant progress had been made in energy consumption control, especially when using adaptive cruise control with a deep neural network system, where driving risks were significantly reduced. For hybrid electric vehicles, ecological driving and energy management were inherently coupled and required coordinated control [34-35], while both vehicle speed and energy management were considered during the optimisation process [36]. This approach was more likely to achieve global optimality than the hierarchical method of separately optimising speed and energy management strategies and then integrating them [37]. This challenge was defined as an optimal control problem [38]. For this purpose, Zhang et al. [39] proposed a nested parallel optimisation approach that effectively reduced the dimensionality of both state and action spaces. The algorithm's novel parallel processing architecture provided enhanced real-time capabilities, enabling coordinated control of speed and energy management in connected hybrid electric vehicles for improved transportation efficiency. Table 2 summarises representative studies on vehicle speed optimisation in the context of vehicle-road collaboration. The key performance indicators for typical vehicle speed optimisation include five aspects: reduce fuel consumption (R.F.C), reduce parking frequency (R.P.F), reduce delay (R.D), reduce safety risk (R.S.R) and improve throughput (I.T).

Table 2 – Typical studies on vehicle speed trajectory optimisation

References	Model/algorithm	Optimisation indicators				
		R.F.C	R.P.F	R.D	R.S.R	I.T
[25]	Feedback algorithm based on Pontryagin's maximum principle	✓				
[26]	Surrogate model for instantaneous optimal energy consumption of the powertrain	✓			✓	
[27]	DP algorithm	✓				
[28]	Multi-stage optimal control model	✓	✓		✓	
[29]	SMPC model	✓		✓	✓	
[30]	Inverse dynamics model	✓				✓
[33]	Enhanced manta ray foraging algorithm	✓	✓		✓	
[39]	Nested parallel optimisation algorithm based on Pontryagin's minimum principle	✓	✓	✓		

Note: R.F.C - reduce fuel consumption; R.P.F - reduce parking frequency; R.D - reduce delay; R.S.R - reduce safety risk; I.T. - improve throughput.

Most current studies on intersection speed guidance systems operate under the assumption that vehicles can receive real-time speed advisories. In the context of intelligent vehicle-infrastructure cooperation, CAVs have emerged as a key element in enhancing future road traffic efficiency. However, during the transition from HDVs to CAVs, mixed traffic flows will inevitably coexist for an extended period. Existing systems often presume 100% vehicle connectivity, overlooking the reality of HDV penetration during the transitional phase. In urban areas with roadside unit coverage below 30%, continuous speed guidance becomes unattainable, and the dual constraints of infrastructure coverage and vehicle connectivity create a "cooperation dead zone". More fundamentally, current speed guidance paradigms still adhere to centralised control logic and have not been able to incorporate HDV driver behaviour into the feedback loop. This "algorithmic myopia" results in the system operating as a high-cost, locally optimal solution during the transition period. To address this challenge, a fundamental rethinking of cooperative paradigms for mixed traffic is required, necessitating the integration of traffic signal control systems to manage HDVs proactively, ensuring seamless coordination with speed guidance strategies.

#### 4. TRAFFIC SIGNAL OPTIMISATION

Traditional traffic lights operate in a fixed, preset phase sequence, failing to prioritise high-volume traffic flows or dynamically adjust green time based on real-time demand. This static control approach significantly degrades overall road efficiency. Moreover, traditional signal control methods rely on fixed timing plans, making them incapable of adapting to dynamic traffic variations. Consequently, they aggravate congestion and result in excessive energy consumption [40].

In the vehicle-road cooperative control (VRCC) environment, adaptive traffic signal control (ATSC) was an advanced intelligent traffic management method [41]. Compared to traditional systems, ATSC not only monitors real-time traffic parameters but also predicts and analyses traffic conditions based on historical and real-time data. By automatically adjusting signal timings, it optimises traffic flow efficiency. In the VRCC environment, traffic signal control is mostly concentrated at the level of isolated intersections and multiple intersections.

ATSC was first proposed in the 1960s [42]. Christian Priemer [43] proposed an adaptive signal control algorithm for vehicle-road cooperative systems, utilising a hybrid approach combining dynamic programming and exhaustive enumeration for optimisation. Compared with traditional signal control methods, their algorithm demonstrates significant improvements in average vehicle speed and delay reduction. Lee et al. [44] proposed a real-time intersection control algorithm that used the cumulative travel-time response (CTR) of connected vehicles. The core of the CTR algorithm was based on stochastic state estimation technology using Kalman filtering. The experimental results showed that there would be better results with 100% market penetration of connected vehicles. When the penetration rate was lower than 30%, the effect of this algorithm was greatly reduced.

Although existing ATSC algorithms have a positive impact on traffic mobility, they do not consider optimising traffic safety. For this purpose, Mohamed et al. [45] proposed a novel self-learning ATSC algorithm to optimise safety at signalised intersections. The trained algorithm was then validated using real-world traffic data collected from two signalised intersections in Surrey, British Columbia, Canada. Compared to traditional actuated signal control systems, the algorithm reduced traffic conflicts by nearly 40%. Qian [46] proposed a coordination system to solve the traffic problem at unsignalised intersections to ensure that traditional vehicles in mixed traffic environments can receive instruction information in advance and pass through the intersection safely. Yektamoghadam et al. [47] used a genetic algorithm and teaching-based optimisation to conduct a multi-criteria optimisation method for traffic lights. Compared to the existing signal timing of the studied intersection, the traffic capacity has improved by 6.76%. Anuj [48] proposed an improved version of linear quadratic regulator (LQR) that supports software-defined networking (SDN), namely the quantified LQR (SDN-QLQR) intersection management system. To further verify the feasibility of the proposed method, experiments were conducted at intersections in the actual traffic network of Gwalior, India. The results demonstrated that the proposed SDN-QLQR improved various performance indicators, including average queue length, average waiting time, throughput and average speed.

Current traffic-light-based optimisation systems overlook the need for regional traffic flow coordination, which compromises overall efficiency. Therefore, Fu [49] proposed a graph convolution network-based adaptive signal timing framework for regional traffic optimisation. An automated control method for bidirectional arterial green waves was proposed. This method uses the dynamic regional traffic signal timing optimisation results and adopts a multi-strategy fusion graphics method to obtain dynamic arterial two-way green waves. Compared with the traditional graphics method, the multi-strategy fusion graphics method achieved a 20% increase in green wave bandwidth. The arterial two-way green wave adaptive collaborative control method enhanced arterial traffic efficiency by 32.3% and regional network traffic efficiency by 8.7%. The work in [50] proposed an arterial traffic type-2 fuzzy coordination control method based on the gravitational search algorithm. Type-2 fuzzy system provided better approximation than type-1 fuzzy system as its three-dimensional membership functions, which made type-2 fuzzy logic control more appropriate for traffic signal control.

In recent years, with the rapid development of deep learning, the application of deep neural networks in traffic signal control has attracted the attention of researchers with the advantages of automatic recognition in high-dimensional traffic data. Research in [51] proposed a solution using a multi-agent deep Q-learning (DQN) algorithm. They proposed an innovative multi-agent reward system, which aimed to balance sustainability with classical performance metrics to achieve more efficient transport network management. Tunc et al. [52] integrated fuzzy logic control with DQN to develop an agent-based adaptive traffic signal timing system, empirically validated for improved control efficiency. Moreno-Malo et al. [53] developed and implemented a

new multi-agent traffic light decision-making system based on Q-learning to minimise the overall waiting time of citizens at traffic intersections, shorten the waiting time, and thereby reduce carbon dioxide emissions, fuel efficiency and noise reduction. The study in [54] proposed a deep reinforcement learning traffic control strategy incorporating type-2 fuzzy control. In this approach, the output action of the type-2 fuzzy control system replaces the action of selecting the maximum Q-value output from the target network in the DQN algorithm, thereby reducing the error caused by the max operator in the target network. This method enhanced the agent's online learning efficiency and increased the reward value for signal control actions.

The pioneering success of deep Q-networks in gaming domains has spurred growing scholarly interest in integrating deep learning with reinforcement learning, culminating in the field of deep reinforcement learning (DRL). Conventional DRL models for traffic control were predominantly confined to homogeneous road networks, exhibiting limited generalisability. Addressing this critical constraint, [55] proposed a novel spatiotemporal graph attention multi-agent DRL framework with value decomposition, effectively extending DRL applicability to heterogeneous urban road networks while preserving coordination efficiency. In heterogeneous road network environments, this algorithm demonstrated even more significant advantages in reducing average vehicle delay, minimising stopping frequency and improving travel speed. In order to achieve more efficient collaboration between traffic lights and alleviate urban traffic congestion, Yan [56] proposed a graph cooperation Q-learning network traffic signal control (GCQN-TSC) model to enhance cooperative traffic signal control and alleviate urban congestion. This model introduced deep graph Q-learning as its core methodology. To further validate the model's effectiveness in real-world road networks, experiments were conducted on a segment of the actual traffic network in Xiasha District, Hangzhou, China. The results demonstrated that GCQN-TSC outperforms other traffic signal control methods across nearly all key performance indicators, including average queue length and waiting time. Wang et al. [57] customised another DQL method and also developed a data-driven prediction model without simulation to reduce the computing time of training DQL. The proposed data-driven model can predict traffic status within limited computing time, and the DQL algorithm is 3.9% better than the field experimental performance of the adaptive control system SCOOT and 22% better than SYNCHRO's time-of-day plan. Merbah et al. [58] proposed a traffic signal control system that combines the accuracy of mathematical modelling with the real-time and adaptability characteristics of deep learning (DL), and bases the DL configuration between the environment and the intersection. The interaction was mathematically modelled as a Markov decision process, taking into account both structural and safety issues.

Recent years have seen notable advancements in traffic signal control, driven by the successful application of reinforcement learning. However, most advances remain predominantly vehicle-centric, neglecting pedestrian mobility and consequently inducing inefficiency as well as safety issues. The work in [59] enhanced urban pedestrian-friendliness by recording pedestrian peak rates and facilitating location-aware traffic light adjustments via advanced interactive visualisation and analysis. Further extending this research, [60] proposed an innovative pedestrian mobility model that not only analysed heterogeneous pedestrian behaviours but also seamlessly integrated them with traditional vehicle-oriented traffic signal control schemes. The distinctive features of their framework lie in its comprehensive incorporation of multi-modal traffic participants, including pedestrians. *Table 3* summarises typical studies on traffic signal optimisation in the vehicle-road cooperative control environment. Based on research subjects in traffic signal control, the studies can be categorised into two types: isolated intersections and regional intersections. By employing optimisation methods such as optimisation theory (O.T.), feedback control (F.C.) and machine learning (M.L.), along with evaluation indicators including queue length (Q.L.), travel time (T.T.), vehicle delay (V.D.), throughput (TRP), parking frequency (P.F.) and security risks (S.R.), the distinct emphases and comparative advantages of typical research approaches can be identified.

7Table 3 – Typical studies on traffic signal optimisation

	References	Optimisation methods			Evaluation indicators					
		O.T.	F.C.	M.L.	Q.L.	T.T.	V.D.	TPR.	P.F.	S.R.
Isolated intersections	[44]		✓			✓	✓	✓		
	[45]	✓								✓
	[46]		✓			✓				
	[47]	✓			✓			✓		
	[48]	✓	✓		✓	✓	✓	✓		
	[51]	✓		✓	✓		✓			
	[52]			✓		✓	✓			
	[57]		✓	✓	✓	✓		✓		
Multiple intersections	[43]	✓				✓	✓			
	[50]	✓		✓		✓	✓			
	[50]	✓		✓		✓	✓			
	[55]	✓		✓		✓	✓	✓	✓	
	[56]	✓	✓	✓	✓	✓				
	[59]	✓			✓		✓	✓		✓
	[60]	✓		✓	✓	✓		✓		✓

Note: O.T.- optimisation theory; F.C.- feedback control; M.L.- machine learning; Q.L. - queue length; T.T.- travel time; V.D.- vehicle delay; TPR.- throughput; P.F.- parking frequency; S.R.- security risks.

Despite significant advancements in ATSC research in recent years, a practical gap persists, hindering its widespread deployment in real-world road networks. Most current ATSC algorithms, such as the CTR method for connected vehicles, rely on idealised assumptions of 100% penetration rates of connected vehicles [44], while in reality, mixed traffic flows consisting of connected vehicles and HDVs pose a long-term challenge.

While some studies (e.g. [45]) have begun incorporating traffic safety optimisations, mainstream ATSC algorithms still primarily prioritise vehicle-centric indicators (e.g. delay, queue length), neglecting the protection of vulnerable road users such as pedestrians and cyclists. Although studies [59, 60] incorporate pedestrian behaviour models, they do not provide a systematic quantification of safety benefits (e.g. conflict reduction rates) or adequately address dynamic pedestrian crossing demands in signal optimisation.

Current research trends lean toward technical stacking (e.g. deep learning + reinforcement learning + fuzzy logic [52, 58]), yet suffer from limited interpretability and engineering feasibility. For instance, [58] combines deep learning with Markov decision processes but does not clearly define how the mathematical models synergise with deep learning components.

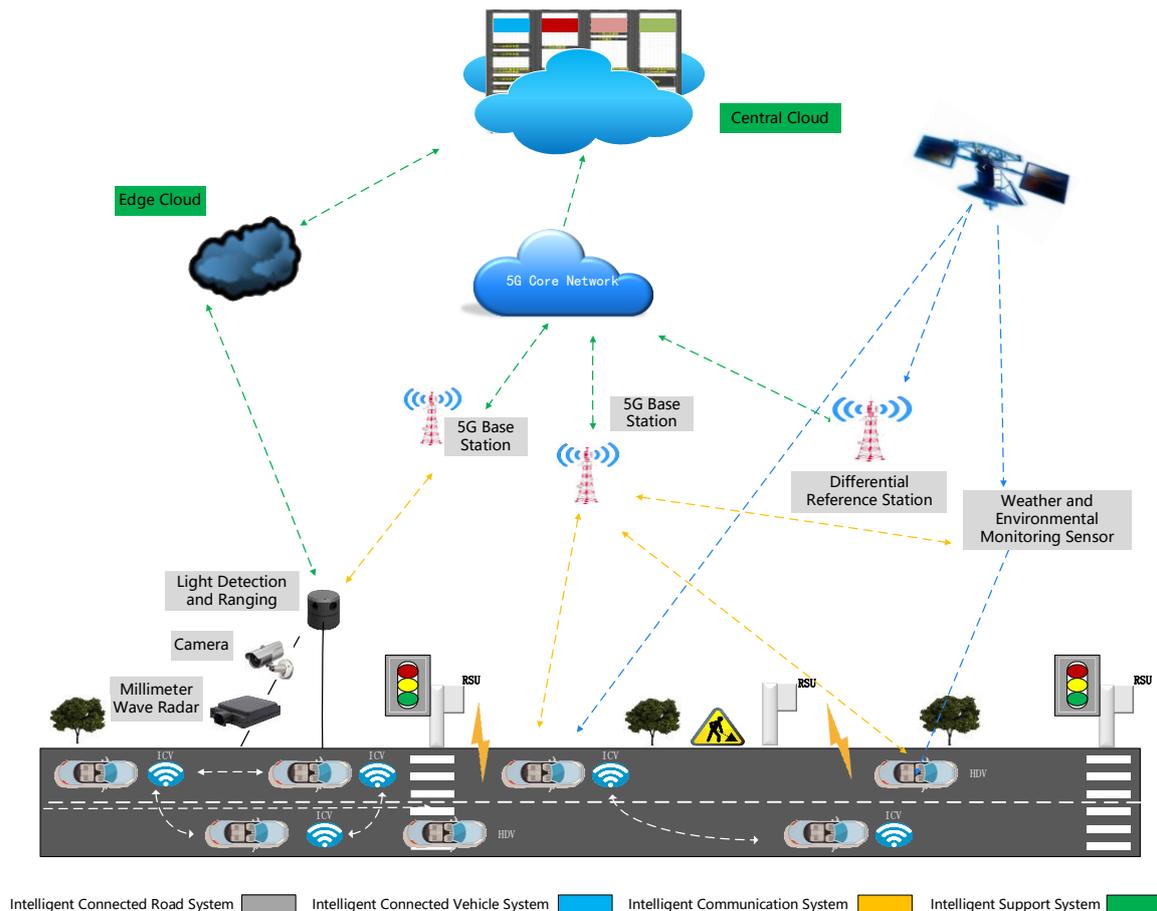
Furthermore, most experiments are conducted in specific case studies (e.g. Gwalior, India [48]; Xiasha District, Hangzhou, China [56]), raising questions about whether the findings can generalise to different urban topologies (e.g. grid-based vs. radial road networks).

### 5. CO-OPTIMISATION OF TRAFFIC SIGNALS AND VEHICLE SPEEDS

In the vehicle-road cooperative environment, ICVs transmit real-time basic information such as vehicle speed, geographic location and driving direction to the vehicle-road cooperative system via vehicular communication networks (V2V/V2I). These vehicles also share data with road infrastructure devices across a network-wide coverage. At the same time, their driving parameters can be precisely controlled by the onboard system or central control unit. A critical distinction from HDVs is that ICVs feature accurate information

perception and decision-making, stable and safe operation, near-zero response latency, and energy-efficient and environmentally friendly power system control, all of which are unaffected by the driver’s skill level. As a result, ICVs are seen as a crucial factor in improving road traffic flow efficiency in the future. *Figure 2* illustrates the heterogeneous traffic flow vehicle-road cooperative ecological environment in the context of intelligent connected vehicles.

Within the vehicle-road cooperative control framework, as ICVs are progressively deployed, optimising either vehicle speeds or traffic signals in isolation proves insufficient for efficient intersection management and traffic flow regulation [61]. Consequently, recent studies have shifted focus toward co-optimising signal timing and vehicular trajectories, demonstrating that this integrated approach maximises green-phase utilisation and enhances intersection throughput.



*Figure 2 – The heterogeneous traffic flow vehicle-road cooperative ecological environment in the context of intelligent connected vehicles*

Li et al. [62] proposed a traffic signal and vehicle trajectory collaborative optimisation algorithm. By comparing the algorithm with traditional drive control, the intersection delay was reduced by 16.2%-36.9% and the throughput was increased by 2.7%-20.2%. Guo et al. [63] proposed an efficient dynamic programming with shooting heuristic (DP-SH) algorithm, which improved traffic efficiency and safety by simultaneously optimising the intelligent networked vehicle trajectory and intersection signals. Even under the condition of low penetration of connected and autonomous vehicles, the DP-SH algorithm still had obvious advantages in energy saving and fuel consumption compared with the adaptive signal control algorithm. Yu et al. [64] proposed a mixed-integer linear program (MILP) model to optimise traffic signals and vehicle trajectories for a single intersection. The MILP model optimised vehicle trajectories and traffic signals in a unified framework for isolated urban intersections with multiple stages and vehicles moving in various directions. Soleimaniamiri et al. [65] optimised the vehicle trajectory model and signal timing with the goal of minimising travel delays and energy consumption. Qian [66] coordinated the optimisation of the departure time, path planning, vehicle trajectory and signal timing of intelligent connected vehicles, and proposed two mixed integer nonlinear programming models for trunk lines and power grids to achieve stable traffic conditions in trunk lines and grid networks.

Xu et al. [67] proposed a coordinated method for traffic signal control and vehicle speed optimisation for networked automatic vehicles to improve urban traffic efficiency and fuel economy. The method consisted of two levels: roadside traffic signal optimisation and on-board vehicle speed control. Salman [68] proposed two information control methods based on simplified logical judgment and fuzzy logic judgment under the COLOMBO framework, and concluded that problems about traffic signals should be treated as logical problems. Sun et al. [69] proposed a new intersection signal and vehicle trajectory coordinated control method in a mixed traffic flow environment. Compared with traditional control methods, this method significantly reduced intersection vehicle delays and reduced green light time waste. Wang et al. [70] aimed to improve the efficiency of intersection traffic and fuel economy through collaborative optimisation and constructed a signal control and vehicle trajectory collaborative optimisation control method. Zuo et al. [71] formed an integrated complex hybrid traffic system by deeply integrating people, vehicles, roads and clouds. It could achieve collaborative perception, collaborative decision-making and collaborative control to improve driving safety. Li et al. [72] proposed a cooperative optimisation method integrating variable guidance lanes with traffic signal control at intersections. Taking the Jianshe Avenue-Xinhua Road intersection in Wuhan, China, which features variable guidance lanes, as the study case, traffic flow data were collected during morning peak, off-peak and evening peak hours. Compared to traditional lane configurations, the variable guidance lanes demonstrated significant improvements in vehicle delay and queue length indicators. In order to more intuitively demonstrate the uniqueness of the literature mentioned in this article, *Table 4* summarises typical studies on the co-optimisation of traffic signals and vehicle speeds. The optimisation indicators primarily include four aspects: travel time (T.T.), vehicle stops (V.S.), throughput (TPR.) and fuel consumption (F.C.).

*Table 4 – Typical studies on co-optimisation of traffic signals and vehicle speeds*

References	Optimisation model/algorithm	Optimisation indicators			
		T.T.	V.S.	TPR.	F.C.
[62]	Trajectory optimisation algorithm and rolling time domain algorithm	✓		✓	
[63]	DP-SH integrated optimisation algorithm			✓	✓
[64]	MILP model	✓	✓	✓	✓
[65]	SMO algorithm	✓			✓
[66]	Nonlinear programming model for a hybrid whole line	✓	✓	✓	
[67]	MPC algorithm, VT-CPFM model			✓	✓
[68]	Simple fuzzy logic control algorithm in the COLOMBO framework	✓		✓	
[69]	Adaptive signal timing model, CAV autonomous speed control model	✓	✓	✓	✓
[70]	Rolling optimisation algorithm, “three-stage” trajectory optimisation algorithm	✓			✓
[71]	CVDS-IDM model	✓		✓	✓
[72]	Particle swarm optimisation	✓	✓	✓	

*Note: T.T.-travel time; V.S.-vehicle stops; TPR.-throughput; F.C.-fuel consumption.*

With the rapid progress of technologies such as intelligent transportation and vehicle-road collaboration, the traffic environment is undergoing major changes. In a new mixed heterogeneous traffic flow environment, the optimisation of vehicle-road control strategies faces many challenges, and the mutual influence between intelligent connected vehicles and human-driven vehicles must be considered. In recent years, some scholars have attempted to construct an intersection control optimisation method under a new heterogeneous traffic environment. Zhang et al. [73] explored the impact mechanism of communication on the stability of mixed traffic flow. The study showed that when the CAV penetration rate reaches 60%, the communication delay can be effectively suppressed. In the context of heterogeneous traffic flow, Shao et al. [74] proposed a variable

speed limit and lane change collaborative control strategy for continuous bottlenecks on highways for CAVs and HDVs. With the goal of minimising travel time and speed difference, a collaborative control framework under continuous bottlenecks was constructed. Mehrdad et al. [75] integrated signal timing and trajectory control optimisation into a mixed integer nonlinear programming model, and decomposed the intersection-level program into multiple lane-level programs, while considering improving computational efficiency and achieving a balance between solution quality.

With the rapid growth of CAVs on urban roads, it is crucial to analyse, model and control heterogeneous traffic. It has been recognised that urban traffic control with heterogeneous traffic is promising, but more effort and research are needed. Although current studies (e.g. [73, 74]) have explored mixed-traffic scenarios involving CAVs and human-driven vehicles, most algorithms rely on simulations or limited real-world data (e.g. the single-intersection case study in Wuhan [72]). This lack of large-scale, long-term real-network validation makes it difficult to demonstrate robustness under complex conditions such as dynamic congestion or extreme weather events.

## 6. CONCLUSION

This paper systematically reviews critical technologies in vehicle-road cooperative control, including right-of-way allocation, vehicle speed trajectory optimisation, traffic signal optimisation, and co-optimisation of traffic signals and vehicle speeds. While existing research has achieved promising results in isolated intersection optimisations, such approaches are often inadequate for real-world complex road networks. Future studies must move beyond localised optimisation paradigms and establish a networked cooperative control framework for CAVs to provide methodological guidance for the intelligent development of urban transportation. In recent years, the VRCC technology has advanced significantly, leading to marked improvements in key traffic performance indicators, including traffic efficiency, throughput, travel time and fuel consumption. While most current studies focus on exclusive ICV environments, VRCC strategy optimisation in mixed traffic environments presents greater challenges. Although substantial research has been conducted on VRCC methods for mixed traffic scenarios, existing solutions still require further optimisation and exploration. Future research efforts should prioritise the following momentous areas.

- 1) Driving behaviour modelling of HDVs and ICVs: Current studies predominantly employ car-following and lane-changing models to characterise vehicle driving behaviour, often assuming that ICVs can fully comply with speed recommendations. Future research should further investigate the multi-source dynamic coupling mechanisms of driving behaviour by developing an adaptive decision-making model, enabling more accurate characterisation of heterogeneous interactions in mixed traffic environments of HDVs and ICVs. Additionally, it is essential to establish an interpretable framework for driving behaviour that integrates multi-dimensional physiological, psychological and environmental parameters, leveraging real-world vehicle experiments to validate behavioural evolution patterns of drivers in ICV-enabled environments and their underlying impact mechanisms on system stability.
- 2) VRCC methods for heterogeneous traffic flows: Existing studies mainly address the vehicle-road cooperative control of road networks under the environment of purely ICVs or single-intersection VRCC for heterogeneous traffic flows, and very few studies have paid attention to the complexity and uncertainty of the vehicle-road cooperative optimisation and control problems specific to the environment of heterogeneous traffic flows in the road network.
- 3) Integration of multi-level traffic control: Most of the existing research focuses on single-level (i.e. single-intersection, arterial or network) traffic control. However, traffic control strategies at different levels (e.g. route planning and area boundary control at the road network level, signal coordination at the arterial level, and signal timing and trajectory planning at the intersection level) are interdependent and can work together to influence the operation of the traffic road network. Few studies have reported the integration of different levels of control strategies to improve traffic operational efficiency.

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## CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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