



A Review of Research on Coordinated Control of Traffic Signals at Urban Road Intersection Groups

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Review

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ABSTRACT

Effective traffic signal coordination is essential for urban intersection groups, helping reduce delays and improve throughput efficiency. This paper systematically reviews the progress in intersection group signal coordination control, focusing on four main aspects. First, an overview of partitioning methods is provided from both static and dynamic perspectives. Next, optimisation-based signal coordination is classified into two main approaches: single-objective and multi-objective control. We then present advanced adaptive signal control strategies, with a focus on deep reinforcement learning techniques. Finally, signal coordination in intelligent and connected environments is explored, addressing three key scenarios: trunk roads, road networks and non-signalised intersections. The research shows that intersection group partitioning is moving toward dynamic and multi-criteria approaches. Signal coordination is shifting toward multi-objective optimisation and proactive adaptive control to address complex traffic environments. Deep reinforcement learning, particularly deep Q-networks and its variants, has been widely applied in adaptive signal control for real-time traffic flow adjustments. In intelligent and connected environments, the collaborative optimisation between intersections is a key research focus. This paper provides a theoretical framework for intersection group signal coordination, with broad applications in improving traffic efficiency, reducing congestion and advancing intelligent transportation systems.

KEYWORDS

urban transportation; road traffic; intersection group; signal control; optimisation algorithm; deep reinforcement learning.

1. INTRODUCTION

The rapid pace of urbanisation and the increasing number of vehicles have made urban traffic management a critical challenge in modern cities. Despite continuous investments in urban road infrastructure, it remains insufficient to meet the growing demand for efficient transportation. Intersections, which serve as key nodes and bottlenecks in road networks, play a pivotal role in managing traffic flow and alleviating congestion. However, with the continuous surge in traffic volumes and the increasing complexity of urban traffic networks, traditional traffic signal control methods, such as single-point signal control, have become insufficient in addressing these emerging challenges. Single-point signal control primarily focuses on managing traffic flow at individual intersections, often overlooking the interactions between adjacent intersections, which can lead to inefficiencies. As such, there is a growing need for more comprehensive and adaptive control strategies that can respond to the dynamic nature of urban traffic systems and optimise traffic flow across interconnected intersections [1].

The concept of intersection groups and their coordinated signal control has emerged as a response to urban traffic challenges. An intersection group is referred to as a set of closely located and interconnected intersections within an urban road network [2]. These groups are characterised by short distances between intersections, high density, relatively small network scale and a higher proportion of minor and secondary roads. They exhibit concentrated traffic demand, effective network connectivity, flexible route choices, distinctive traffic flow characteristics, minimal differences in road hierarchy and relatively even network load distribution. Coordinated signal control for intersection groups is a strategy that treats adjacent intersections as a unified system for signal management. This approach considers the traffic conditions at individual intersections and accounts for the dynamic traffic flow within the entire intersection group and the interactions between adjacent intersections.

As unique entities within road networks, intersection groups differ from traditional control subareas within regional signal coordination systems, particularly in how they are delineated. A control subarea is typically formed by dividing the entire road network into several subnetworks, whereas intersection groups are identified within the network based on their connectivity characteristics. Intersections within the same control subarea typically share similar traffic flow characteristics, while those within the same intersection group are defined through the identification of bottlenecks and their corresponding impact zones [3]. Compared to traditional control subareas, grouping multiple intersections into an intersection group for coordinated control can better identify congested areas within the network. This approach allows for the development of targeted and effective signal coordination strategies based on the network structure and traffic demands of these congested areas.

As a significant innovation in urban traffic management, intersection group signal coordination control aims to optimise traffic flow through refined and systematic methods. It not only adjusts the signal cycles of individual intersections but also dynamically coordinates the optimisation of multiple intersections within a group by considering factors such as traffic flow, demand and road network structure. This approach effectively alleviates traffic congestion, reduces delays and improves road throughput efficiency. With the rapid development of intelligent transportation systems, the research on intersection group signal coordination control has made significant progress, leveraging advanced technologies such as deep reinforcement learning and intelligent connected technologies, further driving innovation and efficiency in traffic management. Therefore, this paper focuses on intersection groups and provides a comprehensive review of the latest research advancements in traffic signal coordination control. It discusses the evolution of signal coordination methods, technological innovations and their applications in various traffic environments. Through summarising and analysing existing research, this paper aims to further advance the theoretical research and practical application of intersection group signal coordination control.

This section outlines the literature search strategy employed for this review. For Chinese literature, the search primarily relied on China National Knowledge Infrastructure (CNKI), a leading academic database in China. The keywords “intersection group” and “signal” were used to ensure that the retrieved papers closely aligned with the theme of coordinated signal control for intersection groups. The search results were carefully filtered, with particular attention paid to classic papers published before 2010 to understand the historical and theoretical foundations of the field. Additionally, the review emphasised selecting core journal articles and conference papers published after 2010 to ensure the inclusion of the latest research findings and cutting-edge developments, thereby guaranteeing the academic quality and impact of the cited literature. After rigorous selection, a total of 80 relevant Chinese and English papers were obtained, providing a solid foundation for the review. In summary, the literature search strategy for this review prioritised the precision of keywords, the comprehensiveness, representativeness and timeliness of the literature, and ensured that the review comprehensively and deeply reflects the current state of research and development trends in the field of coordinated signal control for intersection groups.

By using the visualisation of similarities viewer (VOSviewer), an in-depth analysis and visualisation of both Chinese and English literature in the field of coordinated traffic signal control at intersections was conducted. The keyword co-occurrence network, as shown in *Figure 1*, was generated from this analysis. This network reveals the research hotspots, core topics and the interconnections between different research themes in this field.

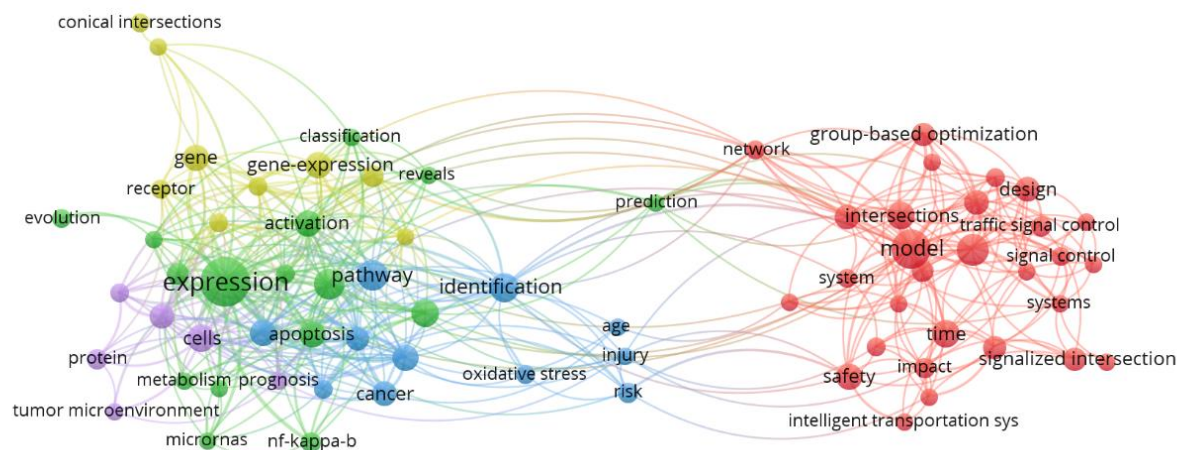


Figure 1 – Keyword co-occurrence network for traffic signal control of the intersection group

As shown from the network, it is evident that research on coordinated traffic signal control at intersections covers a wide range of topics. Firstly, the high frequency of keywords such as “objective function” and “optimisation model” indicates that researchers place significant emphasis on defining appropriate objective functions and constructing effective optimisation models to guide traffic signal control strategies. These models aim to maximise traffic flow efficiency, reduce congestion and emissions, and enhance traffic safety.

Secondly, mathematical solutions and heuristic algorithms also emerge as key research areas. The co-occurrence of the keywords “mathematical solution” and “heuristic algorithm” suggests that researchers are exploring various mathematical methods and algorithms to solve these complex optimisation problems. These approaches include not only traditional mathematical programming methods but also more recent advancements such as metaheuristic algorithms, machine learning techniques and deep reinforcement learning algorithms, which provide innovative solutions for traffic signal control.

Moreover, other critical keywords such as “intersection characteristics”, “traffic flow dynamics” and “real-time control” also appear in the network. The presence of these terms indicates that researchers are equally focused on the characteristics of intersections, the dynamic nature of traffic flow and the design of real-time control strategies. These studies contribute to a deeper understanding of traffic patterns at intersections, shed light on the core research topics and trends in the field of coordinated signal control and inform the development of signal control strategies that better align with real-world traffic demands.

The research framework of this study is structured as follows. First, following the process of coordinated signal control for groups of intersections, we provide a comprehensive review of the research on intersection group partitioning methods and coordinated signal control within these groups. The review of intersection group partitioning methods explores the current state of both static and dynamic partitioning techniques. In the study of coordinated signal control for intersection groups, the research is classified based on methodological approaches and application scenarios, focusing on three main areas: optimisation model-based control, deep reinforcement learning-based control and control within intelligent connected environments. The optimisation model-based approach is further divided into single-objective and multi-objective signal coordination, depending on the number of optimisation goals within the model. For signal coordination control within intelligent connected environments, the research is categorised by the control area, including signal coordination for arterial roads, network-wide signal coordination and coordination for intersections without traffic signals.

This paper systematically summarises key fields based on the characteristics of various studies. In the research on intersection group partitioning methods, key fields such as the constructed models, factors considered in the models and partitioning methods were selected. In the study of coordinated signal control for intersection groups, focusing on optimisation models and the connected intelligent vehicle environment, the research areas were categorised by problem scenarios, control scope, constructed models, specific optimisation objectives, solution algorithms and control methods. Additionally, research based on deep reinforcement learning was summarised by outlining key elements such as the environmental state, agent actions, reward functions and reinforcement learning techniques. Finally, the paper systematically reviews the current research achievements and discusses future trends in coordinated signal control for intersection groups.

2. THE METHODS FOR PARTITIONING INTERSECTION GROUPS FOR SIGNAL COORDINATION CONTROL

Partitioning intersection groups for signal coordination control is a crucial preliminary task for implementing coordinated signal control. It involves grouping multiple intersections with high similarity and strong interconnections into units that require unified signal control. As the fundamental units of network-wide coordination, the accuracy of intersection group delineation directly impacts the effectiveness of the coordinated control. Improper partitioning can lead to traffic signal confusion, exacerbate congestion and even cause traffic accidents. Research indicates that the need for coordination and the extent of control for adjacent intersections are determined based on their level of interconnection [4].

Correlation reflects the degree of mutual influence between intersections in terms of traffic flow, including factors such as traffic volume, flow direction and travel speed [5]. By conducting an in-depth analysis of these factors, the correlation between intersections can be accurately determined, which in turn helps decide whether coordinated control is necessary and the extent of control required. In practical applications, various methods can be used to assess the correlation between intersections, such as statistical analysis based on traffic volume or simulation testing based on traffic models. These methods provide traffic managers with a more precise understanding of the traffic characteristics between intersections, offering robust data support for the scientific partitioning of intersection groups.

The technique for partitioning intersection groups consists of two core steps: the calculation of correlation metrics and the application of intersection group partitioning algorithms [6]. Correlation, as a key metric, effectively reflects the degree of connectivity between adjacent intersections, quantifying their suitability for being grouped into the same intersection cluster. The objective of intersection group partitioning algorithms is to divide the urban road network into several tightly connected control zones based on the correlation model through a scientific and systematic process. During this process, the factors influencing intersection correlation encompass both static and dynamic aspects. Static factors mainly include intersection spacing and road hierarchy, while dynamic factors involve traffic volume, queue length and more. Based on these factors, intersection group partitioning methods can be categorised into static and dynamic approaches [7]. Static partitioning divides the road network into fixed subzones based on predefined rules, while dynamic partitioning adjusts subzone boundaries in real-time according to changes in traffic conditions and time-based rules.

2.1 Static partitioning methods for intersection groups

Static partitioning of intersection groups refers to the process of dividing intersections into groups such that the boundaries of these groups remain fixed over time. Once an intersection is assigned to a group, both the number of intersections within the group and the group's area remain constant in subsequent periods. This method primarily relies on static factors, such as intersection spacing and road classification, to determine groupings.

Under static partitioning, the coordination control strategies are also relatively fixed. This approach is suitable for scenarios where traffic flow is stable and does not exhibit significant variations. By establishing groups based on consistent criteria, static partitioning ensures that the control strategies remain applicable to the long-term traffic patterns and operational characteristics of the intersections within each group.

To more comprehensively assess key factors such as segment length and traffic volume between intersections, Yagoda et al. innovatively employed coupled indicators to explore the correlation between intersections in depth [8]. Clustering and discriminant analysis methods were considered to scientifically group intersections. Tian and Urbanik further investigated the intersection correlation model by considering multiple factors, including intersection spacing, travel speed, cycle length and segment traffic volume [9]. Meanwhile, Ji and Geroliminis proposed a road network partitioning method based on spectral clustering, which accurately solves the characteristic system of the similarity function's weight matrix [10]. By utilising the vehicle density attributes of road segments, this method achieves a more balanced density distribution across the partitioned network. Yang et al. combined discrete and obstruction-related correlation indicators to construct a more comprehensive intersection group path correlation model, which was suitable for describing the correlation characteristics of multiple intersections and multiple paths [11].

Saeedmanesh and Geroliminis designed an innovative three-step clustering algorithm to analyse congestion propagation characteristics, particularly suitable for road network partitioning scenarios with wide coverage and significant data gaps [12]. Tang et al., based on existing discrete and obstruction-related indicators, proposed the introduction of a main path indicator to more comprehensively characterise the correlation

between road segments [13]. The self-organising map (SOM) neural network, using hierarchical clustering and successfully identifying bottleneck areas in the road network, was optimised by integrating the maximum flow minimum cut theory. Wang and Chen proposed an intersection classification algorithm based on traffic data. This algorithm determined the number of categories using multiple evaluation metrics and within-cluster sum of squares, followed by applying the partitioning around medoids (PAM) algorithm to accurately classify intersections [14]. These studies not only improve the accuracy of road network partitioning but also provide more scientific foundations for traffic management decisions.

In summary, the static partitioning of intersection groups primarily relies on methods such as correlation models, similarity models or clustering analysis models. When constructing these models, multiple factors are comprehensively considered, including specific metrics such as road segment traffic volume, length, traffic density, intersection spacing, travel speed and cycle length. Additionally, the models incorporate multidimensional indicators such as discreteness, obstruction, main paths and similarity. During the partitioning process, static partitioning algorithms play a central role, with clustering algorithms such as spectral clustering, three-step clustering and hierarchical clustering being commonly used. Moreover, simulation tools like CORSIM provide effective technical solutions for solving static partitioning problems of intersection groups. In brief, the static partitioning process involves first building a correlation model for intersections by considering one or more road segments or operational indicators, followed by using appropriate clustering algorithms to define the partition boundaries.

2.2 Dynamic partitioning methods for intersection groups

In complex real-world road networks, the relationship between traffic supply and demand, as well as traffic management strategies, is often in a state of constant change. This dynamic nature also results in real-time fluctuations in the correlation between intersections. Therefore, the partitioning of intersection groups should not remain static but should actively respond to changes in macro-level traffic flow by adopting dynamic partitioning methods. Dynamic partitioning allows for the flexible adjustment of the composition and boundaries of intersection groups based on real-time traffic conditions, enabling a more precise adaptation to traffic flow changes and improving the efficiency and effectiveness of traffic management.

In urban intersection coordination control, the degree of dispersion of vehicle fleets along road segments is commonly used to characterise the link correlation between adjacent intersections. As early as 1973, Whitson et al. proposed a model for calculating segment correlation, focusing on the traffic volume of various directions at upstream intersections to effectively describe the correlation of the main coordination direction [15]. However, the classic Whitson correlation model has limitations in accurately depicting the key origin-destination (OD) path directions at downstream intersections. To address this issue, Hu et al. introduced a new model that fully considers the distribution of major OD paths on local road networks and successfully implemented dynamic partitioning of intersection groups using hierarchical clustering methods [16]. Ma et al. viewed the road network area partitioning as a multi-objective problem constrained by multiple factors. Three spectral methods for area partitioning were employed based on the correlation between adjacent intersections, and found that the mean partitioning method performed the best [17]. Lu et al. proposed a correlation-based coordination subarea partitioning model and developed a process to determine the optimal subarea division scheme. They innovatively combined dimensionality reduction techniques with genetic algorithms, enabling rapid optimisation of subarea partitioning and enhancing the efficiency of traffic management [18].

Shou and Xu drew inspiration from the proximity theory in group dynamics to clarify the constraints for subarea partitioning and designed a layered, step-by-step partitioning strategy. Clustering algorithms for in-depth analysis and evaluation of the partitioning scheme were further applied, providing new insights and methods for subarea division [19]. Shen and Yang analysed the influencing factors of intersection correlations, examining the effects of segment distance, traffic density and signal cycles on these correlations. Based on this analysis, they established a fuzzy algorithm-based subarea partitioning method, providing a fresh perspective on the partitioning of intersection groups [20]. Saeedmanesh and Geroliminis considered the dynamic changes over time and employed deterministic clustering for stable road segments, then applied the principle of minimising the objective function to merge or split less stable segments, resulting in more precise subarea partitioning [21]. Dimitriou and Nikolaou compared the performance of the K-means algorithm and the METIS algorithm in road network partitioning, concluding that while K-means excels in clustering objects with simple numerical attributes, it struggles to address the combined challenges of spatial connectivity and traffic flow characteristics in transportation networks [22]. To more accurately quantify segment correlations, Hu et al. constructed a correlation model based on real-time traffic operational data from adjacent intersections on

arterial roads [23]. Qu et al. innovated on traditional correlation models by considering factors such as vehicle dispersion, obstruction, and the distribution of starting and ending points. A path correlation model was established, and dynamic partitioning of intersection groups was successfully implemented using hierarchical clustering methods [24]. Meanwhile, Lan and Wu employed correlation analysis and regression analysis to develop a correlation model for adjacent intersections, utilising the analytic hierarchy process to design the principles and procedures for traffic zoning, subsequently proposing an innovative traffic zoning model [25].

In summary, research on the dynamic partitioning of intersection groups is more prevalent than that on static partitioning, as it better adapts to the time-varying traffic demands in real time. Dynamic partitioning primarily establishes correlation models and may also create undirected graph networks. The factors considered in these models include segment length, traffic density, signal cycle, average flow, dispersion indicators, obstruction indicators, coordination coefficients and imbalance coefficients, with the inclusion of key OD path indicators that enhance the considerations found in static partitioning. The algorithms for dynamic partitioning of intersection groups mainly involve clustering methods such as hierarchical clustering, K-means clustering, three-step clustering and spatial clustering. Additionally, methods from complex network theory, such as community detection, the METIS algorithm, regression analysis and solutions based on Synchro, can also be applied. Overall, beyond clustering algorithms, the dynamic partitioning of intersection groups can initially identify bottleneck points in the road network and define the influence range of these bottlenecks based on the strength of correlation indicators, thereby delineating the areas of strongly correlated intersection groups. Therefore, the partitioning of intersection groups for signal coordination control is a complex yet crucial task. A scientifically sound division of intersection groups, coupled with optimised coordination control strategies, can significantly enhance the overall operational efficiency and safety of urban traffic.

3. SIGNAL COORDINATION CONTROL OF INTERSECTION GROUPS BASED ON OPTIMISATION MODELS

Fixed-point detection in signal control primarily relies on detection devices, such as inductive loops and cameras, installed at fixed locations to collect and record traffic flow data. These data can include vehicle passage times, vehicle types, speeds and more, providing the signal control system with real-time or near-real-time traffic information for more effective traffic management and control. Compared to mobile detection, fixed-point detection offers advantages such as high stability and strong data reliability. However, it also has drawbacks, including relatively high maintenance costs and limited coverage.

Model-driven signal coordination control for intersection groups involves establishing specific mathematical models that consider different objective functions, utilising dedicated optimisation algorithms for timing, sensing and adaptive control. Depending on the number of control objectives, model-driven signal control can be categorised into single-objective optimisation and its solutions, as well as multi-objective optimisation and its solutions.

3.1 Single-objective signal coordination control for intersection groups

Single-objective optimisation focuses on a single performance metric within the model, and it is one of the earliest research areas in traffic signal control. It often evaluates congestion levels in intersection groups using metrics such as the saturation degree, which measures the ratio of overall traffic demand to the road network's capacity.

When the saturation degree is less than 1, the system is considered under-saturated, indicating smoother traffic flow and primarily facing constraints related to time resources. Conversely, when the saturation degree exceeds 1, the system is over-saturated, suggesting that spatial resources are constrained, and problems such as overflow and queue delays are more likely to occur [26].

Most researchers primarily focus on single-objective signal control for intersection groups in under-saturated states. Keyvan et al. designed a boundary-gated algorithm based on a macro fundamental diagram, which was activated when predicted traffic flow density exceeded a specific threshold, limiting the number of vehicles entering congested areas [27]. Han et al. addressed the issue of total vehicle delay in an area by developing a multi-intersection signal timing model that considers the impact of non-motorised vehicles, optimising it through an improved genetic algorithm [28]. Yan et al. discovered that in heterogeneous road networks, the overall network capacity improves with the homogenisation of vehicle density distribution. In response, researchers developed adaptive signal control rules to balance queue lengths across all incoming directions, leveraging iterative learning control theory to enhance interaction with the traffic environment [29].

Additionally, Lu et al. established an intersection importance assessment model based on road network topology and successfully implemented traffic flow balancing and signal coordination control using a directed depth search algorithm [30].

Additionally, some researchers have conducted single-objective signal control studies focusing on the oversaturated state of intersection groups. Ma et al. aimed to minimise the delay deviation of vehicles passing through intersection groups by designing two priority strategies for “late” and “early” vehicles: reducing bus delays and increasing bus delays. Five sub-models were established and ultimately solved using a recursive enumeration method [31]. Lei et al. developed a mathematical model for main road intersection groups in oversaturated conditions, targeting the minimisation of trip delays while ensuring that vehicle queues do not overflow beyond the operational limits. A method for solving extremum problems in nonlinear programming was employed to achieve this [32].

Liu et al. focused on over-saturated traffic conditions, using vehicle queue length as a parameter to determine the optimal release phase based on the queue states of current and adjacent intersections, thereby facilitating adaptive coordinated control among neighbouring intersections [33]. Furthermore, some researchers have explored single-objective signal control in response to public transport priority demands. Liu et al. addressed the multi-application problem for public transport priority in intersection groups by constructing a signal control model based on path priorities, aiming to minimise total bus delays and solving it through dynamic programming methods [34]. Bie et al. developed an algorithm to integrate bus priority and the presignal method at signalised intersections. They evaluated the performance of the proposed approach under various traffic conditions to improve bus service efficiency [35]. Behbahani and Poorjafari proposed a kinematic wave-based adaptive transit signal priority control using a genetic algorithm. The proposed method aimed to optimise the signal timing to improve the efficiency of transit priority under varying traffic conditions [36].

In summary, single-objective optimisation and solution methods for signal coordination control of intersection groups have addressed both under-saturated and over-saturated traffic scenarios. In terms of model establishment, there exist three-tier control structures and intersection importance estimation models, with a predominant focus on conventional multi-intersection signal timing models. The specific objectives selected for these models primarily include minimising travel time, reducing vehicle queue lengths and minimising total delay for motor vehicles in the region. The solution algorithms employed consist mainly of mathematical methods, such as nonlinear programming, as well as heuristic algorithms, including genetic algorithms, directed depth search algorithms and boundary gating algorithms. Real-time control methods are more commonly used, while fixed-time control methods are less prevalent. Additionally, some studies have explored scenarios prioritising public transport, establishing two-level priority strategies or optimisation control models for multiple public transport requests, aiming to minimise intersection group delay deviations or total bus delays, and utilising recursive enumeration or dynamic programming methods for real-time signal control. Overall, after years of research, the theories related to single-objective optimisation have become quite mature and are approaching saturation.

3.2 Multi-objective signal coordination control for intersection groups

As traffic signal control technology continues to advance and the demands for signal management become increasingly stringent in practical applications, the coordinated control of intersection groups must take into account various factors, including safety, fluidity and efficiency. It is essential to achieve comprehensive coordination of multiple objectives while optimising key traffic signal parameters, such as green signal ratios, phase differences and cycle durations. Consequently, conducting in-depth research on multi-objective signal optimisation holds significant practical relevance.

To address the common scenario of undersaturation in intersection groups, several scholars have explored multi-objective signal control. Gao et al. developed a multi-objective signal coordination optimisation model aimed at maximising the total throughput of each intersection while minimising average vehicle delay, average queue length and average stopping rate. A non-dominated sorting genetic algorithm was employed to identify the Pareto optimal frontier [37]. Chiou established a minimum-maximum bi-level programming model that accounts for the uncertainty of traveller behaviour choices to investigate equilibrium traffic flow control under uncertain demand, demonstrating robust performance [38]. Hu et al. proposed a bus priority control strategy incorporating green wave coordination by leveraging vehicle-road collaboration technology. Their bi-level programming model minimised bus delays at intersections and upstream segments in the upper-level objective

function, while the lower-level function minimised total delay across the intersection group, using a diagonal iteration method [39].

Jia et al. introduced an innovative multi-objective signal timing optimisation model that considers per capita delay, vehicle emissions and intersection capacity, proposing a novel heuristic algorithm that combines particle swarm optimisation (PSO) with differential operators for model resolution [40]. Wu et al. developed an intersection signal control optimisation model focused on minimising emissions. An emission calculation method was considered based on intersection stopping conditions, considering vehicle stopping and running states at entry points to compute total emissions, solved via a genetic algorithm [41]. Lastly, Yu et al. applied video recognition technology to predict short-term traffic flow along various paths within the intersection group. A clustering algorithm was used to identify key paths and optimise based on delays and queue lengths on these paths, designing a cellular genetic algorithm for resolution [42]. Collectively, these studies offer robust theoretical support and practical guidance for multi-objective signal control in the undersaturated conditions of intersection groups. To address the unique challenges of saturation and oversaturation in intersection groups, several scholars have conducted in-depth research on multi-objective signal control strategies. Chen et al. developed a heuristic hierarchical control algorithm, consisting of a control layer and a coordination layer, specifically for oversaturated mainline intersection groups. This approach incorporates both mainline and secondary road delays as objectives and employs a multi-objective compatible control strategy based on the improved Pareto-based non-dominated sorting genetic algorithm II (IPNSGA-II) genetic algorithm for optimisation [43].

Within traffic networks, a path that experiences maximum traffic volume and exerts a decisive influence on overall operational conditions is referred to as the critical path. Given that the critical path may change over time and may not consistently align with specific road directions, rapid and accurate detection of this path is fundamental for effective coordinated control. Li et al. established a path hierarchy model utilising wavelet transformation and spectral analysis to investigate the signal control mechanisms and implementation frameworks for intersection groups under oversaturated traffic conditions. Their approach features a three-layer control structure comprising a single intersection layer, a critical path layer and an intersection group layer, with the goal of maximising the number of vehicles passing along the critical path while minimising average queue length [44]. Zhao et al. focused on the maximum queue length and average delay at the entrance of intersection groups as input variables. Fuzzy C-means clustering was applied to determine the fuzzy sets and membership functions associated with these inputs, and a two-tier fuzzy controller for traffic signal control was implemented [45].

Jia et al. proposed a real-time control framework and methodology for oversaturated intersection groups, employing a linear-axis combination method to achieve rolling optimisation of phase differences and cycle times [46]. Collectively, these studies provide effective strategies and methodologies for addressing the multi-objective signal control challenges encountered by intersection groups under saturation and oversaturation conditions. Some studies have further considered bus priority control. For example, Seman et al. developed an integrated control strategy combining headway and bus priority in transit corridors with bidirectional lane segments. The approach aimed to improve bus service efficiency by adjusting signal timings to prioritise buses while maintaining smooth traffic flow for all vehicles [47]. Xu et al. introduced a decentralised signal control model based on the max-pressure control principle, focusing on maximising vehicle throughput and improving bus transit reliability by integrating transit signal priority [48].

In summary, within the subfield of multi-objective optimisation, numerous scholars have specifically investigated oversaturated intersection groups. The established multi-objective models encompass bi-level and tri-level control structures, fuzzy control and critical path-based optimisation models. Typically, the number of objectives ranges from 2 to 4, with 2 being the most common. Some researchers concentrate on average metrics for the entire intersection group or individual intersections, including throughput, average delay, number of stops and queue length. In contrast, others focus on metrics related to key intersections or critical paths, such as the maximum number of vehicles passing through the critical path and the delays experienced along it. The optimisation efficiency of the critical path method is superior to that of overall network optimisation, making it particularly suitable for adaptive real-time control scenarios.

Some studies prioritising bus traffic focus on minimising bus delays and enhancing the operational stability of public transit, while others aim to reduce environmental impact by targeting minimal exhaust emissions. In terms of solution algorithms, commonly used methods include two-tier fuzzy control, synchronous perturbation approximation algorithms, Nash-Stackelberg algorithms and genetic algorithms, with improved variants of these methods seeing more frequent application. Regarding control strategies, most multi-objective

signal control studies emphasise fixed-time control, while multi-objective real-time control strategies, despite their increasing importance in dynamic traffic environments, remain relatively underexplored.

4. SIGNAL COORDINATION CONTROL FOR INTERSECTION GROUPS BASED ON DEEP REINFORCEMENT LEARNING

Fixed-point detection in signal control primarily relies on detection devices, such as inductive loops and cameras, installed at fixed locations to collect and record traffic flow data. These data can include vehicle passage times, vehicle types, speeds and more, providing the signal control system with real-time or near-real-time traffic information for more effective traffic management and control. Compared to mobile detection, fixed-point detection offers advantages such as high stability and strong data reliability. However, it also has drawbacks, including relatively high maintenance costs and limited coverage.

Deep reinforcement learning (DRL) combines reinforcement learning with deep learning, leveraging the powerful representational capabilities of deep learning to manage complex perception and state spaces while using reinforcement learning mechanisms to discover optimal decision-making strategies. In the realm of signal coordination control for intersection groups, DRL can dynamically adjust traffic signal control parameters based on real-time traffic conditions and demands to achieve optimal traffic flow. The DRL-based approach for signal coordination can be divided into four key steps: state perception, feature extraction, policy learning, policy execution and evaluation.

In this framework, the agent represents the traffic signal, while the environment comprises the intersections within the traffic network that are equipped with traffic signals. The state captures the environmental information at a given time, such as vehicle positions, speeds and queue lengths. The reward is closely associated with performance metrics like average vehicle waiting time or queue length. After observing the traffic network's state, the agent makes decisions that are then communicated to the environment. The environment provides feedback to the agent based on the quality of these decisions. During decision-making, the agent integrates the observed state and reward information to determine the optimal action for the subsequent time step, thereby maximising the reward. *Figure 2* illustrates the DRL framework for traffic signal control.

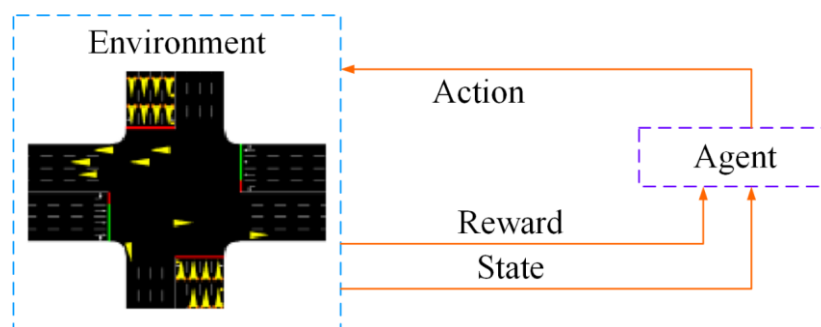


Figure 2 – Deep reinforcement learning framework for traffic signal control

Nishi et al. adeptly employed graph convolutional networks (GCN) to extract geometric features of the road network directly. The N-step neural fitted Q iteration (NFQI) algorithm for batch data processing was utilised to update Q-values, thereby achieving efficient and precise distributed traffic signal control [49]. Chu et al. introduced a multi-agent advantage actor-critic based on deep Q-network (DQN), which integrates the latest policies of neighbouring agents and the current state into the deep neural network (DNN). By proportionally scaling the information from more distant agents, this method successfully constructs inter-agent relationships based on a hybrid reward function [50]. Wu et al. incorporated long short-term memory (LSTM) networks into the critic and actor networks of the multi-agent deep deterministic policy gradient (MADDPG) algorithm and introduced a parameter-sharing mechanism, resulting in the MADDPG algorithm, which enhances the model's stability in partially observable environments [51]. Devailly et al. utilised inductive graph reinforcement learning (IG-RL) to dynamically model the topology of vehicles, lanes and traffic signals at intersections. GCN was applied to share parameters among nodes of the same category and objects within the same intersection, leveraging vehicle-level information through distributed reinforcement learning training to achieve intelligent traffic signal control [52].

Arel et al. implemented a centralised Q-learning network for multi-intersection control. The central agent learned the value function based on traffic information from nearby agents and estimated Q-values by combining Q-learning with feedforward neural networks. Neighbouring agents, on the other hand, controlled signals using the longest queue first strategy [53]. Tan et al. employed a double DQN approach, defining the state as a combination of signal phases, queue lengths and average vehicle speed. They introduced noise into the queue length information and conducted adversarial training using a multi-layer neural network [54]. Ge et al. proposed a cooperative deep Q-network (QT-CDQN) for adaptive multi-intersection signal control, modelling the traffic network as a multi-agent reinforcement learning system. Algorithm stability was enhanced by utilising target network strategies and an experience replay mechanism [55].

Gong et al. applied a double duelling DQN to enhance model stability and implemented an action freezing period to restrict the selection of certain actions [56]. Kim and Jeong combined double duelling DQN with prioritised experience replay, utilising features such as time and temperature for traffic prediction, and applied NoisyNet to handle the high-dimensional action space. This combined approach effectively addressed the overestimation issue in multi-intersection signal control [57]. Li et al. introduced global state information during the training phase and used discrete tables to store phase information from other agents. Information sharing was achieved through a value function approximator, with each agent employing a DQN learning strategy [58]. Xie et al. proposed an information exchange method that uses the previous time step's observation data instead of the current one. A model comprising three components was designed: an information abstraction block, an information exchange block and a DQN. This model integrates information between intersections with local observations, assuming it as a fully observable state [59].

Li et al. employed the MADDPG algorithm, which operates within a centralised training and decentralised execution framework. This approach simultaneously trains a critic network that requires global information and an actor network that relies solely on local information. Given that each agent possesses an independent reward function, this algorithm is applicable to fully cooperative, fully competitive and semi-competitive/semi-cooperative tasks [60]. Rasheed and Yau utilised multi-agent cooperative learning to determine the optimal joint actions, deriving the global Q-value from the sum of individual agents' Q-values. In light of the challenges posed by heavy rain, this method effectively alleviates the curse of dimensionality in high-traffic, high-interference scenarios [61]. Zang et al. adopted a value-based meta-learning approach, dividing the meta-learning process into training and testing phases. Their goal was to train a universal meta-learner by alternately updating parameters through individual and global adaptation modules [62].

Wang et al. proposed a cooperative independent double Q-learning method (Co-DQN) based on mean field theory, which employed the upper confidence bound method to define agent actions. In this framework, each agent's reward function is represented as the sum of its own reward and a weighted reward from neighbouring agents [63]. Long et al. proposed a DRL approach for optimising transit signal priority in a connected traffic environment. Their approach dynamically adjusts traffic signal timings to minimise delays for public transit while ensuring efficient overall traffic flow [64]. Yu et al. proposed a decentralised deep reinforcement learning approach for multi-modal traffic signal control, incorporating bus priority in urban networks. The method optimises signal timings for different transportation modes to enhance network efficiency and reduce delays [65].

5. COORDINATED SIGNAL CONTROL FOR INTERSECTION GROUPS IN INTELLIGENT AND CONNECTED ENVIRONMENTS

Driven by advancements in electronic information and wireless communication technologies, vehicle-road cooperation and vehicle networking have become pivotal in steering intelligent transportation toward a new direction. Vehicle-road cooperation facilitates real-time perception and collaborative control between vehicles and road infrastructure, thereby enhancing traffic safety and efficiency. Concurrently, vehicle networking provides real-time traffic demand data, establishing a traffic information network that supports intelligent driving. The integration of vehicle-road cooperation, vehicle networking and autonomous driving technologies optimises signal configuration based on real-time traffic demand information, representing a crucial strategy for enhancing urban traffic control performance.

Research on signal control within intelligent connected environments initially focused on single-point intersections. Zhang et al. proposed a dual-ring adaptive signal control method specifically for single-point intersections in connected environments. This approach involved calibrating the car-following model and constraining green light durations to compute the optimal phase length. Experimental results demonstrated that

this method significantly reduced delays and the number of stops compared to fixed-time control, with optimisation effects improving as saturation levels and vehicle connectivity penetration rates increase [66]. Following the refinement of single-point intersection studies, researchers have broadened their perspectives, turning their attention to more complex scenarios such as arterial roads, road networks and uncontrolled intersections, with the aim of achieving deeper applications and performance enhancements of intelligent transportation in diverse traffic environments.

5.1 Coordinated signal control for arterial roads

In the context of intelligent and connected mixed traffic flow environments, signal coordination control for arterial roads can be approached using either utility optimisation or bandwidth optimisation methods. The utility optimisation method estimates changes in vehicle arrivals at intersections or simulates sampled trajectories with the objectives of maximising flow or minimising delay. In contrast, the bandwidth optimisation method focuses on optimising signal timing to maximise green wave bandwidth.

Considering the different traffic demands of passenger cars and special vehicles, He et al. utilised commercial vehicle (CV) trajectory data to identify vehicle arrivals at intersections and the priority of special vehicles. A mixed-integer linear programming (MILP) model was developed to optimise cycle length, phase duration, sequence and phase offsets, aiming to minimise weighted total delay while assigning higher weights to special vehicles to ensure their priority passage [67]. Kari et al. addressed the limitations of traffic detection by proposing an agent-based adaptive signal control strategy, which adjusts traffic light settings according to traffic demand. Results indicated that this strategy outperformed the Highway Capacity Manual (HCM) method in terms of vehicle delay and fuel consumption and exhibits strong robustness to real-time changes in traffic demand [68]. Wu et al. constructed an integrated optimisation model to maximise the product of flow and speed along coordinated paths. This model included bidirectional coordinated paths, dynamic vehicle speeds and intersection timing parameters, aiming to maximise the number of vehicles passing without stopping and minimise delays. It overcomes issues found in traditional methods, such as fixed vehicle speeds, significant impacts from queue lengths and insufficient path coordination optimisation [69].

Li and Ban harnessed the position and speed information of connected vehicles to formulate a signal timing optimisation method aimed at minimising the weighted sum of total fuel consumption and travel time, employing a dynamic programming model for resolution. Traffic simulation assessments demonstrated that this model outperformed the Synchro-generated solutions [70]. In contrast to indirect timing methods that depend on traffic flow parameter estimates, Yao et al. derived the relationship between sampled trajectories and arterial signal timing parameters using traffic wave theory, targeting the minimisation of trajectory delays. A multi-population PSO algorithm was implemented to optimise cycle lengths, durations, sequences and phase differences. Although their control performance was slightly lower than that of Multiband, this model exhibited stability across varying trajectory penetration rates, confirming the viability of using sampled trajectory data for optimising arterial signal timing [71]. Qi et al. estimated mixed traffic flow parameters from detector data, integrating the Newell car-following model and the Akcelik acceleration model to derive vehicle delays. Their objective was to minimise delays by optimising cycle lengths, phase durations and phase differences, utilising a PSO algorithm for resolution [72].

Yao et al. developed an adaptive signal control optimisation method aimed at minimising average delays by predicting vehicle arrivals through a dynamic queue model for connected vehicles, employing a rolling genetic algorithm for resolution. The VISSIM indicated that this method reduced average delays by 22.7% and queue lengths by 24.8% when compared to traditional adaptive algorithms [73]. Recognising that traffic flow on arterial routes may not consistently reach maximum levels, Wang et al. defined the concept of critical paths, using CV trajectory data to estimate vehicle arrival information and optimising arterial signal timing through a bi-level model. The optimisation goal was to maximise the bandwidth of the critical path, employing dynamic programming for resolution. At the intersection level, an adaptive model was developed to minimise total vehicle delays, while at the arterial level, a MILP model was employed to maximise critical path bandwidth and optimise coordinated phase differences [74]. Zhang et al. proposed a DRL-based adaptive signal control method to improve bus priority service efficiency in a connected vehicle environment. The research optimised the bus priority signal control strategy and validated it under various traffic scenarios [75].

5.2 Signal coordination control for road networks

Traffic signal coordination control at the network level can be categorised into centralised and distributed types. Centralised network signal coordination can achieve a global optimal solution. Yan et al. introduced a network-level multi-band signal coordination scheme, which aimed to maximise the weighted sum of continuous flow bandwidth while minimising green wave displacement to optimise phase durations and phase differences. This scheme was transformed into a multi-objective MILP model and solved using a custom decomposition-based heuristic algorithm [76].

However, as the scale of road networks expands significantly, the computational burden of centralised signal coordination methods continues to increase, making it increasingly difficult to satisfy real-time control requirements. Consequently, some researchers have developed distributed network signal control models that decompose large-scale network signal optimisation problems into a series of smaller intersection signal optimisation subproblems, thereby enhancing solution efficiency. Mohebifard et al., by utilising real-time vehicle arrival data and connected vehicle trajectory information, employed a cellular transmission model to estimate vehicle arrival distributions at intersections. A MILP model was formulated, aimed at maximising network capacity, optimising the start and end times of green lights at intersections, and introducing a distributed model predictive control algorithm to enhance solution efficiency [77].

Similarly, Islam et al. constructed a cellular transmission model, deriving the evolution of mixed traffic flows from real-time detected vehicle arrival times and connected vehicle trajectory data. A signal timing optimisation model was established, aimed at maximising network capacity, which was solved using the CPLEX Optimiser [78]. Unlike the first two scholars, Moradi et al. proposed a distributed network signal control method based on trajectory data. This method included a three-layer control framework: intersection controllers estimate queue lengths and identify special vehicles; the network controller manages traffic flow based on the network fundamental diagram; and the phase controller employs Kalman filtering to predict vehicle arrival rates and optimise phase start timing [79]. Chen et al. proposed a network-level control approach that guaranteed bus priority in a heterogeneous automated traffic system. It leveraged reinforcement learning to dynamically adjust traffic signals and improve overall system efficiency while ensuring smooth bus operations [80].

5.3 Coordinated control for unsignalised intersections

Simultaneously, both domestic and international scholars are actively exploring effective ways to utilise connected vehicle data for managing signal-free intersections, aiming to further enhance traffic efficiency and safety.

At the point-control level, Mirheli et al. proposed a trajectory control scheme for autonomous vehicles at signal-free intersections, aiming to maximise intersection capacity. This scheme leveraged connected vehicle information to achieve speed trajectory control under safe conditions, employing a Monte Carlo tree search algorithm to optimise acceleration. The results demonstrated that this method can prevent accidents and reduce travel time by 59.4% [81]. Li et al. established a trajectory coordination model in an extended spatiotemporal dimension and proposed a signal-free intersection control method based on priority algorithms and distributed free-range optimal control (DFROC) algorithms. Simulation of Urban MObility (SUMO) simulations showed that these two algorithms effectively reduce delays and improve traffic efficiency compared to first-come-first-served and timed signal control [82].

In a fully connected environment with Level 5 fully autonomous driving, traffic signals may not be essential in the absence of other road users. Nevertheless, even with fully automated vehicles, signals are crucial for communicating right-of-way to other system users. This suggests that while technological advancements are making traffic environments smarter and safer, traffic signals continue to play an irreplaceable role in ensuring the orderly and efficient flow of traffic.

At the trunk level, Beak et al. proposed a method that integrated adaptive signals with trunk coordination. Initially, intersection-level coordination was performed through dynamic programming, followed by optimising the phase differences for trunk signals and updating coordination constraints. VISSIM simulations indicated that this approach significantly reduces average delays and the number of stops compared to traditional trunk signal coordination [83]. Wang et al. targeting the minimisation of average vehicle delay, introduced a continuous intersection traffic signal control model based on upper and lower-layer neural networks. The signal switching decision-making process was modelled as a Markov decision process, thus overcoming the limitations of reinforcement learning in trunk coordination control. Simulations revealed that

this model effectively enhanced intersection capacity across various saturation levels [84]. The coordinated control methods for signal-free intersections proposed by various researchers are summarised in *Table 1*.

Table 1 – Coordinated control for unsignalised intersections

Researcher	Control range	Built model	Number of targets	Specific objectives	Solution method	Control mode
Mirheli et al. (2018)	Point control	Trajectory control model	one	Maximum intersection capacity	Monte Carlo tree search algorithm	real time
Li et al. (2019)	Point control	Trajectory coordination model	one	Minimum average delay	Priority algorithm and DFROC algorithm	real time
Beak et al. (2017)	Mainline control	Dynamic programming model	two	Minimum average delay and average number of stops	Dynamic programming method	real time
Wang et al. (2021)	Mainline control	Markov decision model	one	Minimum average delay per vehicle	Upper and lower layer neural network algorithms	real time

6. DISCUSSION

Signal coordination control within the intersection group plays a crucial role in improving traffic flow management through the implementation of various strategies and techniques. This integrated approach not only boosts traffic efficiency but also helps to alleviate congestion. Research into the segmentation of intersection groups and their corresponding signal coordination methods has seen significant progress. This paper provides a comprehensive review of both domestic and international studies in the field, focusing on four key areas: methods for partitioning intersection groups for signal coordination, optimisation model-based strategies, deep reinforcement learning approaches and signal coordination in intelligent connected environments. Through systematic organisation, summary and analysis of literature in this field, the following discussions are made.

Partitioning intersection groups for signal coordination is a critical aspect of urban traffic management, directly influencing traffic flow efficiency and safety. This paper explores both static and dynamic partitioning methods, highlighting their strengths and limitations. Static methods, based on fixed parameters such as road spacing and traffic volume, are well-suited for stable traffic environments. However, they lack the flexibility to adapt to real-time fluctuations in traffic demand, which is increasingly important in modern urban networks. On the other hand, dynamic partitioning offers more adaptability by adjusting intersection groupings based on real-time data, though it introduces higher computational complexity.

The research on signal coordination control for intersection groups has evolved from single-objective models focused on congestion management to more complex multi-objective models addressing a broader range of traffic factors, including safety, efficiency and environmental impact. Single-objective optimisation methods, which typically target metrics like vehicle delay and queue length, have laid the groundwork for traffic control, particularly in under-saturated conditions. However, as traffic systems grow more complex, multi-objective models have become necessary. These models integrate factors such as public transport priority and emission reduction, providing a more comprehensive approach to traffic management.

DRL has been demonstrated to be effective for optimising traffic signal coordination in intersection groups, adapting to dynamic traffic conditions. Various approaches, including multi-agent DQN and GCN, have advanced the efficiency of signal control systems. However, challenges such as scalability and stability persist, especially in complex, real-world traffic networks. Techniques like parameter sharing and experience replay have helped address these issues, while integrating V2X communication and LSTM networks has improved model robustness.

The integration of connected vehicle systems is revolutionising signal control for intersections, with a shift from single-point to more complex road network optimisation. Techniques like MILP, agent-based adaptive control and real-time data-driven models have significantly improved traffic flow, reduced delays and prioritised special vehicles. In arterial roads, both utility and bandwidth optimisation methods, utilising connected vehicle data, enhance signal timing efficiency. Distributed control models are increasingly

important for large-scale networks, offering real-time optimisation of traffic signals. At unsignalised intersections, trajectory coordination for autonomous vehicles has shown promise in improving safety and efficiency.

To sum up, the ongoing evolution of traffic signal coordination strategies is driving significant improvements in urban mobility. Dynamic and real-time optimisation approaches are increasingly vital as traffic environments grow more complex and interconnected. The integration of machine learning, reinforcement learning and connected vehicle technologies presents exciting opportunities for enhancing signal coordination, reducing delays and improving overall traffic efficiency. As cities move towards smarter, more autonomous transportation systems, continued research and innovation in these areas will be essential for creating sustainable and efficient urban mobility solutions.

7. CONCLUSIONS

This paper presents an in-depth and comprehensive study on the topic on coordinated control of traffic signals at urban road intersection groups. Through a thorough exploration of existing literature, methodologies and emerging technologies, the research sheds light on the current state of signal coordination at urban intersections. The findings provide valuable insights into the various strategies for optimising traffic flow, improving efficiency and addressing the challenges posed by the increasing complexity of urban transportation systems. Based on the analysis, the following conclusions have been drawn.

- 1) Methods for dividing intersection groups for signal coordination control are generally classified into static and dynamic partitioning. Dynamic partitioning is more widely explored due to its ability to adapt in real-time to changing traffic demands. Partitioning models consider various indicators, including segment flow, segment length, segment traffic density, intersection spacing, travel speed and cycle length, as well as factors such as correlation and similarity, discreteness and congestion, coordination coefficient and imbalance coefficient. Unlike static partitioning, dynamic models incorporate primary OD path indicators into their objectives. Partitioning algorithms primarily include clustering algorithms and their variations, with some studies employing Synchro simulations to assess correlations. Overall, intersection group division involves establishing a correlation model for intersections based on one or more road segments or operational indicators, followed by the application of clustering algorithms to define the boundaries of intersection groups. In dynamic partitioning, in addition to clustering algorithms, bottleneck points may first be identified within the road network. The impact zone of these bottleneck points is then determined based on the strength of correlation indicators, which helps define the scope of intersection groups with strong correlations. Research on intersection group division is increasingly focusing on dynamic partitioning, comprehensive model indicators, diverse correlation models and the use of heuristic algorithms for problem-solving.
- 2) The signal coordination control of intersection groups based on optimisation models can be divided into two types: single objective control and multi-objective control. The research on single objective control mainly considers objectives such as minimising travel time, minimising vehicle queue length and minimising total delay of regional motor vehicles. Mathematical methods or heuristic algorithms are used to solve the model, and most of them are real-time control methods. Multi-objective control research generally selects two objectives, mainly considering benefit indicators such as traffic capacity and average delay for the entire intersection group, as well as indicators based on the critical path, such as the maximum number of vehicles or travel delay on the critical path. It can also consider bus priority and the reduction of exhaust emissions from motor vehicles. Overall, research on intersection signal control based on optimisation models has shifted from single-objective optimisation to multi-objective optimisation, and from passive timing control mode to active adaptive control mode. Signal period, phase difference and green signal ratio are still key parameters for coordinated control of intersection signals, and heuristic algorithms are widely used in solving multi-objective models.
- 3) The application of DRL to traffic signal coordination control for intersection groups primarily involves algorithms based on value functions and policy gradients. Environmental states defined in this context include queue length, average speed, vehicle count, vehicle positions and signal phases. Agent actions are typically defined as either maintaining the current phase or selecting a phase from a predefined cycle. Reward functions generally encompass metrics such as accumulated waiting time, total delay and average queue length. In multi-intersection scenarios, both local and global rewards are often utilised. Local rewards reflect the traffic conditions at each intersection, such as net traffic flow, to improve the stability

of individual agents. Global rewards are used to help agents learn the optimal strategy for the entire network through cooperative learning, such as the difference in queue lengths between orthogonal directions. Most research focuses on local reward functions. Common DRL methods employed include deep Q-networks and their variants, with the majority of studies resulting in adaptive control solutions.

- 4) In intelligent connected environments, signal coordination control for intersection groups depends on real-time perception of interactions between vehicles and between vehicles and road infrastructure. The optimisation objectives typically include reducing average delay at intersections, decreasing queue lengths and minimising the number of stops, all aimed at enhancing intersection efficiency and service levels. Additionally, these solutions incorporate various constraints, such as cycle length and maximum or minimum green light durations, to ensure the rationality and safety of signal timing. Optimisation efforts generally start at the level of individual intersections and progressively extend to major roads and the entire road network. By considering the coordination and interactions among multiple intersections, the overall efficiency of the traffic system can be significantly improved. Furthermore, as objective functions are refined and updated, these solutions can more comprehensively address diverse traffic conditions and demands, leading to more precise and effective signal timing.

This study highlights the importance of optimising signal coordination control at urban intersection groups, particularly in large-scale and dynamic traffic environments. Future research should focus on improving the precision and efficiency of intersection group division methods, with an emphasis on developing advanced algorithms for dynamic grouping processes and large-scale urban applications. Furthermore, integrating group division with the coordination control process can reduce mismatches between stages, leading to more effective and efficient signal coordination strategies.

In addition, more emphasis should be placed on incorporating environmental benefits into signal coordination models, aiming to reduce traffic-related pollution and create more sustainable urban transportation systems. The integration of signal control with traffic guidance technologies, such as V2I communication and autonomous driving systems, represents a promising frontier. By combining these elements, future research could develop adaptive, intelligent systems that optimise traffic flow, improve safety and contribute to environmentally friendly urban mobility.

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