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Multi-vehicle traffic signal control at multiple intersections: coordinated, adaptive, and intelligent approaches—a review

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ABSTRACT

The increasing number of vehicles in urban areas has intensified congestion, particularly at interconnected intersections where traffic conditions change continuously. Conventional fixed-time traffic signals often fail to respond adequately to fluctuating demand, resulting in unnecessary delays, long queues, and inefficient road utilization. This review examines traffic signal control for multiple vehicles and multiple intersections, focusing on coordinated timing, adaptive control, optimization techniques, and multi-agent reinforcement learning. The discussion covers traffic sensing, signal phase management, inter-intersection communication, network-level coordination, and performance evaluation. Particular attention is given to the differences between isolated intersection optimization and network-wide traffic management, since locally effective decisions may produce congestion elsewhere in a connected road network. The review also considers practical constraints, including uncertain vehicle arrivals, sensor reliability, pedestrian requirements, emergency vehicle priority, and computational scalability. Existing studies indicate that adaptive and cooperative approaches can improve traffic performance under suitable operating conditions, although their benefits depend on accurate traffic information and realistic evaluation. Future systems should combine reliable detection, safe signal constraints, scalable coordination, and field validation to achieve sustainable urban traffic management.

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1. INTRODUCTION

Urban traffic congestion is strongly influenced by the interaction between vehicle demand, road capacity, and the timing of signalized intersections. When several intersections are located along the same corridor or within a connected road network, the operation of one signal can affect traffic conditions at neighboring locations. A poorly coordinated signal may release a large vehicle platoon into a downstream intersection that is already congested. Consequently, traffic signal management should consider the overall road network rather than treating every intersection as an independent facility [1], [2].

Traditional fixed-time traffic controllers operate according to predetermined cycle lengths, phase sequences, and green-time allocations. Although this approach is relatively simple and suitable for predictable traffic patterns, it cannot respond effectively to sudden changes in vehicle demand. Adaptive traffic signal control offers an alternative by using real-time traffic information to modify signal timing according to current conditions [3], [4]. The main challenge is to coordinate these adjustments across multiple intersections without creating conflicting decisions or transferring congestion to other road segments.

This review examines the development of multi-vehicle and multi-intersection traffic signal control, from conventional coordination to intelligent and cooperative approaches. It focuses on the technical relationship between vehicle detection, signal timing, network communication, optimization, and performance evaluation. The central research problem is how to improve traffic flow across an interconnected network while maintaining safety, operational stability, and fairness among different road

users. The review also identifies implementation challenges that must be addressed before advanced control strategies can be adopted in real urban environments.

2. TRAFFIC SIGNAL CONTROL PROBLEMS IN INTERCONNECTED NETWORKS

A multi-intersection traffic network contains several signalized junctions connected by road segments that transport vehicles between locations. Each intersection has competing traffic movements that require appropriate signal phases and green-time allocations. The controller must consider vehicle arrivals, queue lengths, turning movements, downstream road capacity, and signal safety constraints. Eom and Kim [1] explain that the intersection traffic signal control problem involves both local signal decisions and the characteristics of the surrounding traffic network.

The main difficulty arises because traffic conditions are dynamic and spatially dependent. A green phase that benefits one approach may increase congestion on another approach or cause downstream spillback when the receiving road segment has insufficient capacity. Network-level control must therefore balance local vehicle queues with the movement of traffic throughout the entire system. This problem becomes more complicated when intersections have different geometries, traffic volumes, pedestrian demands, and operating constraints [1], [2].

Traffic signal control performance is commonly evaluated through average vehicle delay, queue length, travel time, throughput, and the number of stops. These indicators provide complementary information because reducing delay at one intersection does not necessarily improve total network performance. Environmental indicators, such as fuel consumption and vehicle emissions, are also relevant when evaluating urban traffic management. A comprehensive controller should therefore consider multiple objectives instead of optimizing only the number of vehicles passing through a single junction [2], [3].

3. CONVENTIONAL AND ADAPTIVE TRAFFIC SIGNAL CONTROL

Fixed-time control is one of the simplest approaches to managing signalized intersections because its timing plan is prepared using historical or observed traffic patterns. Coordinated fixed-time systems can synchronize neighboring signals through cycle lengths, green splits, and offsets to support vehicle progression along arterial roads. The SCOOT method is an established example of real-time network signal optimization that adjusts signal settings in response to measured traffic conditions [5]. These approaches provide an important foundation for modern traffic coordination, although their effectiveness depends on detector coverage and the quality of traffic measurements.

Adaptive traffic signal control improves responsiveness by modifying signal timing according to changing traffic conditions. Vehicle detectors, cameras, and other sensing technologies can estimate traffic volume, occupancy, speed, or queue length. The controller uses these observations to determine whether a phase should be extended, terminated, or changed. Reviews by Wang *et al.* [3] and Qadri *et al.* [2] describe the development of self-adaptive and computational-intelligence-based approaches for managing traffic signal timing.

Adaptive control can operate through centralized or decentralized architectures. In centralized control, a traffic management center collects information from multiple intersections and calculates coordinated signal decisions for the network. This architecture can support global optimization, but it requires reliable communication and sufficient computational resources. Decentralized control allows each intersection to make local decisions, potentially improving flexibility and reducing dependence on a central controller. However, neighboring controllers must exchange or consider relevant traffic information to avoid decisions that are locally efficient but harmful to network performance [6], [7].

4. OPTIMIZATION AND INTELLIGENT CONTROL APPROACHES

Optimization-based methods seek signal timing plans that improve selected traffic performance indicators while satisfying operational constraints. Genetic algorithms, fuzzy logic, mathematical programming, and other computational intelligence techniques have been applied to signal timing and traffic management. These methods can search for solutions in complex traffic networks where conventional analytical approaches may be insufficient. However, the quality of an optimized plan depends on the accuracy of traffic demand estimates and the assumptions used in the traffic model [2], [3].

Reinforcement learning provides another approach by allowing a controller to improve its decisions through interaction with a traffic environment. In this framework, an agent observes traffic conditions, selects a signal action, and receives feedback based on the resulting traffic performance. Arel *et al.* [6] demonstrated a reinforcement-learning-based multi-agent system for network traffic signal

control, while Prabuchandran *et al.* [8] investigated multi-agent Q-learning for traffic signal coordination. These studies illustrate the potential of learning-based approaches to improve traffic control beyond predetermined signal timing plans.

Multi-agent reinforcement learning is particularly relevant when each intersection is represented by an autonomous agent. Agents may use local queue information while exchanging selected information with neighboring intersections or learning through a shared network objective. El-Tantawy *et al.* [7] developed the MARLIN-ATSC framework and examined its application to a large urban network in downtown Toronto. Medina and Benekohal [9] also investigated the use of reinforcement learning with the max-plus algorithm as a coordination strategy. These approaches address the need to combine local decision-making with coordinated network behavior.

Deep reinforcement learning extends this concept by using neural networks to represent complex traffic states and decision policies. Cooperative deep reinforcement learning has been investigated for large-scale traffic grids, where a single centralized agent may face an excessively large action space [10]. Chen *et al.* [11] proposed decentralized deep reinforcement learning for large-scale traffic signal control, while Tan *et al.* [12] introduced a cooperative framework using regional and global agents. These studies demonstrate how hierarchical and decentralized learning can help address the scalability problem in networks containing many intersections.

5. MULTI-INTERSECTION COORDINATION AND SYSTEM ARCHITECTURE

A practical multi-intersection traffic control system requires coordinated sensing, communication, processing, and signal execution. At the field level, detectors or cameras collect information about vehicles approaching and leaving each intersection. Local controllers process these observations and communicate relevant traffic conditions to neighboring controllers or a central management platform. The signal optimization module then determines suitable phase changes and green-time allocations while ensuring that conflicting traffic movements are not released simultaneously.

Coordination is particularly important along arterial roads where vehicles travel through successive signalized intersections. When signal offsets are appropriately configured, vehicles may encounter fewer stops and experience improved progression along the corridor. However, fixed progression plans may become less effective when traffic demand changes significantly or when incidents disrupt normal traffic flow. Self-organizing approaches and cooperative learning methods attempt to adapt signal behavior to local and neighboring traffic conditions [13], [14].

Network-wide optimization must also consider the risk of queue spillback. When a downstream road segment becomes saturated, releasing additional vehicles from an upstream intersection may block other movements and reduce network throughput. Max-pressure control addresses this problem by considering differences in traffic queues across connected links when selecting signal phases. An application of the max-pressure approach to six intersections in Bandung, Indonesia, demonstrated its potential to manage disturbed network conditions in simulation [15]. This is particularly relevant to dense urban networks where congestion can propagate rapidly between nearby intersections.

Table 1 compares representative traffic signal control approaches and summarizes their operating principles, strengths, and limitations. The comparison indicates that no single method is universally optimal for every network configuration or traffic condition. Conventional coordination remains useful in relatively predictable corridors, while adaptive and learning-based approaches offer greater flexibility when traffic demand changes. The choice of control architecture should therefore reflect network size, sensing capability, communication reliability, and operational requirements.

Table 1. Comparison of traffic signal control approaches for multiple intersections

Control approach	Operating principle	Main advantage	Main limitation
Fixed-time coordination	Predetermined cycle, split, and offset settings	Simple and predictable operation	Limited response to changing demand
Traffic-responsive control	Adjusts timing using detector measurements	Responds to observed traffic conditions	Depends on reliable sensing
Centralized optimization	Calculates coordinated timing for a network	Supports network-wide objectives	High communication and computation requirements
Decentralized adaptive control	Each intersection makes local decisions	Flexible and scalable architecture	Coordination between neighboring signals is difficult
Multi-agent reinforcement learning	Agents learn local policies with cooperation	Supports distributed decision-making	Training complexity and non-stationary learning
Max-pressure control	Selects phases using traffic pressure on connected links	Addresses queue imbalance and spillback	Requires suitable queue measurements and practical constraints

6. EVALUATION AND IMPLEMENTATION CHALLENGES

Simulation is an important tool for evaluating traffic signal control before field deployment. Microscopic traffic simulators can represent individual vehicle movements, lane changes, queues, and interactions with signal phases. Qadri *et al.* [2] reported the widespread use of microsimulation in traffic signal timing research, demonstrating its importance for comparing alternative control strategies. However, simulated improvements should be interpreted carefully because results depend on network geometry, demand profiles, vehicle behavior, and model calibration.

A reliable evaluation should compare proposed controllers with appropriate baseline methods under consistent traffic conditions. Relevant scenarios include low and high demand, directional imbalance, turning movements, incidents, and changing traffic patterns. Performance should be measured across the complete network rather than only at selected intersections. Studies on deep reinforcement learning and multi-agent control have demonstrated promising results in simulation, but they also reveal the importance of testing different network sizes and traffic conditions [10]–[12], [16].

Several practical challenges remain before intelligent control systems can be deployed widely. Sensor failures, communication delays, inaccurate vehicle detection, and power interruptions may cause controllers to operate with incomplete information. Learning-based systems also require substantial training data and may perform poorly when real traffic conditions differ from their training environments. Wu *et al.* [17] examined robustness in multi-agent reinforcement learning and highlighted the sensitivity of learning-based control to noisy sensor information. Safety constraints, minimum green times, yellow intervals, pedestrian clearance, and emergency vehicle priority must remain enforceable regardless of the optimization method.

7. FUTURE RESEARCH DIRECTIONS

Future research should develop scalable coordination strategies that combine local responsiveness with network-wide objectives. Hierarchical control may provide a practical compromise by allowing local agents to manage individual intersections while regional or central agents coordinate broader traffic patterns. Connected vehicle information could improve traffic-state estimation by providing vehicle positions, speeds, and intended movements. However, the system should retain a reliable fallback mode when communication or connected-vehicle data are unavailable.

Another important direction is multi-objective traffic management. Future controllers should consider not only vehicle delay and throughput but also pedestrian waiting time, public transportation priority, emergency response, emissions, and equitable access to road capacity. Joo *et al.* [18] investigated reinforcement learning for smart-city traffic signal control, illustrating the potential of data-driven methods in connected urban environments. Further work should emphasize real-world testing, transparent evaluation procedures, and the ability to explain why a controller selects a particular signal action.

8. CONCLUSION

Traffic signal control involving multiple vehicles and multiple intersections is a network-level optimization problem that requires coordination among connected traffic facilities. Fixed-time and conventional coordinated methods provide useful foundations, but their limited responsiveness can reduce effectiveness when traffic demand changes dynamically. Adaptive control, optimization algorithms, max-pressure methods, and multi-agent reinforcement learning offer alternative strategies for improving traffic flow and reducing congestion. The reviewed literature indicates that coordinated and cooperative approaches are particularly relevant when traffic conditions at one intersection influence neighboring road segments.

Successful implementation depends on accurate vehicle detection, reliable communication, safe signal timing, and appropriate evaluation across the entire network. Advanced learning methods may improve adaptability, but their performance must be validated under noisy measurements, unexpected traffic conditions, and realistic operational constraints. Future systems should combine decentralized responsiveness with network-level coordination and multi-objective performance assessment. Such development can support more efficient, safer, and sustainable urban traffic management.

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