Consensus-Driven Adaptive Signal Control for Scalable Intersection Management

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***Abstract*—This paper presents a hybrid two-layer traffic signal control architecture combining localized consensus-based vehicle communication with centralized adaptive control for efficient intersection management. We introduce a novel front-priority weighted average consensus algorithm, prioritizing vehicles closest to intersections to enhance delay responsiveness. Structured through an Extended Chain topology, our approach avoids communication bottlenecks and maintains a constant message load independent of traffic density. Simulation results demonstrate significant reductions in average and maximum waiting times—achieving up to 57.1% improvement in average delay—while ensuring fairness across intersection approaches, making our solution highly scalable and practical**

I. Introduction and Motivation

Urban traffic signal control has long been a central focus in transportation systems engineering. Early models such as TRANSYT, SCATS, and SCOOT introduced structured strategies for intersection management through fixed-time or stage-based control schemes. These foundational systems were primarily designed for predictable traffic patterns and centralized coordination [1]. Despite decades of refinement, Traffic signal control still struggles with responsiveness, especially under high traffic variability and in dynamic urban environments.

The societal and economic costs of outdated or inefficient signal timing are considerable. According to a recent survey, drivers in congested U.S. cities such as Boston lose up to 164 hours annually due to traffic delays, resulting in substantial economic losses per individual [2]. Moreover, intersections with suboptimal timing strategies contribute to millions of hours of cumulative delay across the country, underscoring the urgent need for adaptive and context-aware control mechanisms.

This challenge becomes even more pressing in mixed traffic environments, where traditional human-driven vehicles (HDVs) coexist with connected vehicles (CVs) and connected automated vehicles (CAVs)[3]. These transitional traffic conditions pose significant control challenges, requiring strategies that operate effectively under partial connectivity [4], [5]. In such contexts, CAVs equipped with V2V (vehicle-to-vehicle) and V2I (vehicle-to-infrastructure) communication capabilities can serve as mobile sensors, sharing real-time data on position, speed, and delay metrics to support decentralized decision-making.

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Recent studies have explored the use of CAV-generated trajectory data and optimization frameworks to reduce delays and improve fuel efficiency at intersections [6], [7]. However, many of these approaches rely on high penetration rates of connected vehicles, limiting their applicability during transitional deployment phases where connectivity is sparse. Furthermore, the integration of motion planning with signal timing remains a challenging task under bandwidth and reliability constraints.

While some frameworks incorporate elements of predictive and decentralized control, they often overlook fairness in phase allocation—specifically, ensuring balanced delays across different directions. This can result in inequitable traffic flows and inconsistent performance. Additionally, few studies conduct systematic evaluations across diverse communication topologies or compare multiple decentralized algorithms under consistent conditions[8].

To address these limitations, this paper proposes a decentralized, two-layer intersection control architecture suitable for low to moderate CAV penetration. The lower layer employs distributed communication protocols to enable vehicles to exchange queue and delay information. The upper layer applies an adaptive phase selection controller that evaluates competing traffic movements using a weighted scoring function based on queue length, average delay, and maximum observed delay. This architecture draws on predictive control principles and data-driven switching mechanisms [9], [10].

II. Problem Formulation

Urban traffic signal control faces significant challenges in modern transportation networks. Centralized control strategies suffer from scalability limitations in large-scale networks where real-time processing becomes impractical, while fully autonomous intersection management remains infeasible due to the inevitable mixed traffic environment. This section formally defines the system model, vehicle dynamics, performance metrics, architectural layers, and the formal optimization problem that guides our approach.

Our approach introduces a two-layer architecture that strategically combines the strengths of centralized optimization with the practical advantages of distributed coordination. In traditional centralized systems, global state observability enables optimal signal timing. However, these systems scale poorly—computational complexity increases rapidly with the number of vehicles, making real-time adaptation difficult in dense or highly variable environments. Moreover, deploying infrastructure capable of monitoring all vehicles with high temporal precision requires extensive sensor networks and communication hardware, which can be prohibitively expensive and challenging to maintain[7].

On the other end of the spectrum, fully decentralized systems distribute all decision-making to individual vehicles. While this reduces infrastructure burden, it introduces significant latency and inconsistency, particularly problematic in safety-critical settings such as traffic intersections where quick, synchronized responses are essential. Our proposed hybrid framework resolves this tension by introducing a distributed consensus layer that enables connected vehicles to locally aggregate information—such as queue lengths and delays—before transmitting a summarized consensus result to a centralized adaptive controller. This design preserves the optimization capabilities of centralized control while achieving communication efficiency and lower latency. It also facilitates compatibility with existing infrastructure, making the system more practical for gradual real-world adoption.

A. Traffic-Flow Model

We model a single four-way intersection with mixed traffic composed of connected and unconnected vehicles. The intersection has traffic approaching from four directions $d \in \{\mathrm{N}, \mathrm{S}, \mathrm{E}, \mathrm{W}\}$ (North, South, East, West). Each direction has dedicated lanes for left turns, through movements, and right turns. We model vehicle arrivals as a Poisson process with rate λ_d, meaning the probability of one vehicle arriving in a small interval Δt is approximately $\lambda_d \, \Delta t$:

$$P\{N_d(t + \Delta t) - N_d(t) = 1\} = \lambda_d \, \Delta t + o(\Delta t). \quad (1)$$

Upon arrival, each vehicle i is assigned a desired movement $m_i \in \{\mathrm{L}, \mathrm{S}, \mathrm{R}\}$ (Left, Straight, Right) according to fixed turning probabilities. The vehicles form FIFO (First-In-First-Out) queues in their respective lanes and can only proceed when granted a green signal by the adaptive controller introduced below. This FIFO assumption reflects typical lane behavior at urban intersections, where vehicles are served in arrival order unless overridden by emergency or priority rules. We assume connected vehicles are capable of sharing queue and delay information via V2X-like communication.

B. Vehicle State and Waiting Time

Each vehicle i in the system is characterized by a tuple $(t_i^{\mathrm{arr}}, m_i, d_i)$ where t_i^{arr} is the arrival time, m_i is the movement type, and d_i is the approach direction. Connected vehicles additionally track and share queue position and experienced delay, which are used by the consensus algorithms to estimate aggregate lane conditions.

For each vehicle i, we denote its arrival time as t_i^{arr} and its departure time (when it passes through the intersection) as t_i^{dep}. The waiting time for vehicle i is defined as:

$$W_i = t_i^{\mathrm{dep}} - t_i^{\mathrm{arr}}, \quad (2)$$

The average waiting time across all vehicles is:

$$\overline{W} = \frac{1}{N} \sum_{i=1}^{N} W_i, \quad (3)$$

where N is the total number of vehicles processed during the simulation period.

C. Performance Metrics

To evaluate the performance of our system, we define five core metrics that capture delay, fairness, throughput, and communication cost:

- **Average Waiting Time** ($\overline{W}$): The mean waiting time across all vehicles, as defined above. This metric directly measures the efficiency of the control strategy in serving traffic demand.
- **Maximum Waiting Time** ($W^{\max}$): The worst-case waiting time experienced by any vehicle:
$$W^{\max} = \max_{i \in \{1, \ldots, N\}} W_i \quad (4)$$
This prevents prolonged delays for individual vehicles and supports equitable service levels across all movements.
- **Throughput** (veh/hr): The total number of vehicles discharged per hour:
$$\text{Throughput} = \frac{\text{Number of vehicles discharged}}{\text{Simulation time (hours)}} \quad (5)$$
Throughput captures the system's capacity to process traffic volume efficiently and serves as a key indicator of intersection capacity.
- **Jain's Fairness Index**: A measure that quantifies equity across different directions:
$$J = \frac{\left(\sum_d q_d\right)^2}{|D| \sum_d q_d^2}, \quad q_d = \text{queue length}_d \quad (6)$$
where $|D|$ is the number of directions and q_d is the queue length in direction d. The fairness index ranges from 0 to 1, with values closer to 1 indicating more equitable distribution of waiting times across all approaches.
- **Communication Cost**: Total number of messages exchanged during the consensus process:
$$\text{Communication Cost} = \sum_k m^k \quad (7)$$
where m^k is the number of messages exchanged in iteration k of the consensus algorithm. This quantifies scalability in bandwidth-limited scenarios and provides a basis for comparing consensus algorithm efficiency.

D. System Architecture

Our approach uses a two-layer architecture that separates the distributed information aggregation from centralized decision-making:

1) **Distributed Consensus Layer**: Vehicles exchange information with neighbors according to a defined topology to aggregate queue and waiting time information. This layer enables scalable, local information processing before transmission to the controller.
2) **Adaptive Control Layer**: An adaptive traffic light controller uses the aggregated information to determine

signal phases and durations. By receiving pre-processed data from the consensus layer, this component can make globally optimal decisions with minimal computational complexity.

This architecture balances the scalability benefits of distributed processing with the optimization capabilities of centralized control. By aggregating information locally before transmission to the controller, we ensure that the system's **computational complexity remains constant** regardless of the number of vehicles at the intersection, addressing a fundamental limitation of traditional centralized approaches. This division of responsibilities allows for efficient real-time control even in high-density traffic scenarios.

E. Communication Topologies

We investigate four communication topologies that govern how vehicles share information within the system. These topologies reflect practical constraints in vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication and directly impact convergence speed, communication overhead, and estimation accuracy. A comparative analysis of their performance is provided in the ***Main Results*** section.

Centralized (Fully Connected) topology assumes that all vehicles can communicate bidirectionally with both the controller and each other. This configuration provides complete state visibility and serves as an idealized baseline for performance evaluation. However, its communication overhead scales poorly with the number of vehicles, making it impractical for large-scale, real-time deployments.

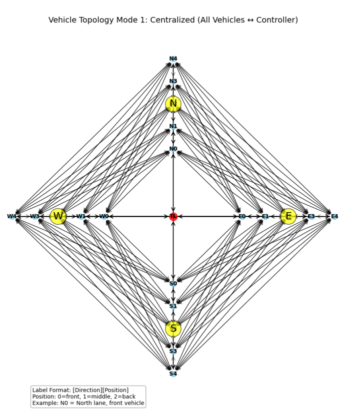

Fig. 1: Fully Connected topology: complete bidirectional communication between all vehicles and the controller, enabling full system observability at the cost of high communication complexity.

Chain topology introduces a more constrained structure where each vehicle communicates only with its immediate predecessor and successor in the same lane. Only the lead vehicle in each lane is allowed to communicate with the controller. This topology significantly reduces communication overhead but introduces longer information propagation delays, particularly in longer queues.

Chain + Front-Priority topology shares the same structural layout as the Chain topology but modifies the consensus algorithm by assigning greater weight to messages from front-line vehicles. This adjustment prioritizes information from vehicles closest to the intersection, which are typically the most time-sensitive in terms of service demand.

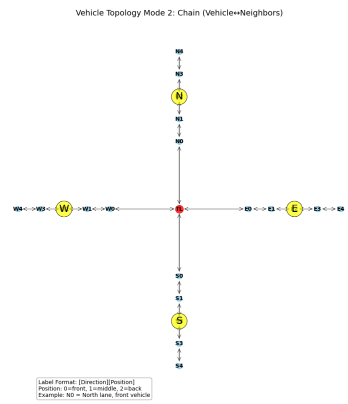

Fig. 2: Chain topology (also used for Chain + Front-Priority): vehicles communicate with adjacent neighbors in the same lane, and only front vehicles report to the controller. The front-priority variant modifies message weighting in the consensus process.

Extended Chain topology enhances the standard Chain structure by enabling direct communication between front vehicles at each approach. These additional lateral links between leading vehicles across directions create a low-latency communication path for critical state information, improving responsiveness without substantially increasing message complexity. This hybrid structure preserves the scalability of the Chain topology while capturing key spatial dependencies needed for efficient signal control.

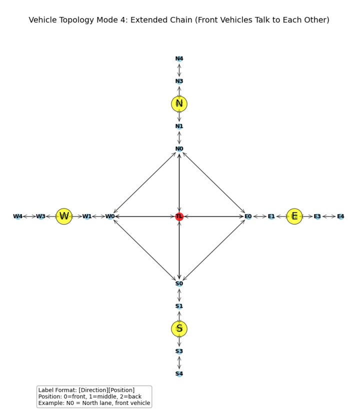

Fig. 3: Extended Chain topology: a hybrid structure that allows front vehicles across approaches to communicate directly, improving cross-directional awareness and reducing information latency.

F. Adaptive Controller

The adaptive controller uses the aggregated information to make decisions about signal phases and durations.

1) Priority Score Calculation: For each movement (d, m), the controller computes a priority score:

$$S_{d,m} = \ \alpha\, n_{d,m} \ + \ \beta\, w_d^{\max} \ + \ \gamma\, \bar{w}_d \tag{8}$$

- $n_{d,m}$: number of vehicles waiting for direction d, movement m
- $\bar{w}_d$: average waiting time in direction d
- $w_d^{\max}$: maximum waiting time in direction d
- α, β, γ: tunable weights that balance queue length, maximum wait, and average wait

The weights ($\alpha = 0.3$, $\beta = 0.2$, $\gamma = 0.2$) were empirically determined through extensive sensitivity analysis to balance responsiveness to queue buildup while preventing starvation of low-volume movements, as discussed in Section 4, where we evaluate the sensitivity of the controller to parameter tuning. The adaptive scoring logic used by the controller is inspired by principles from model predictive control (MPC) and decentralized optimization[11], integrating real-time traffic data to balance efficiency and fairness.

2) Green Phase Duration: After selecting the set of non-conflicting movements $\mathcal{M}$ with highest scores, the controller determines the green phase duration:

First, compute aggregated queue and waiting time metrics:

$$Q = \sum_{(d,m)\in\mathcal{M}} n_{d,m}, \quad \bar{w} = \frac{\sum_{(d,m)\in\mathcal{M}} \bar{w}_d\, n_{d,m}}{Q \vee 1}. \tag{9}$$

Then, normalize these values and compute a combined scaling factor:

$$\begin{aligned} &r = \min\!\Big(1,\ \tfrac{Q/|\mathcal{M}|}{10}\Big), \quad u = \min\!\Big(1,\ \tfrac{\bar{w}}{30}\Big), \\ &\phi = 0.7\, r + 0.3\, u. \end{aligned} \tag{10}$$

Finally, determine the green phase duration:

$$T_{\text{green}} = T_{\min} + \phi\, (T_{\max} - T_{\min})\,. \tag{11}$$

- $T_{\min}, T_{\max}$: configured minimum/maximum green times
- $Q/|\mathcal{M}|$: average queue-size per movement
- $r \in [0, 1]$: normalized queue factor
- $u \in [0, 1]$: normalized wait-time factor
- ϕ: combined scaling factor

This controller logic ensures responsive signal timing based on real-time traffic conditions, adaptively allocating green time proportional to demand and waiting time urgency.

G. Optimization Objective

Our primary optimization objective is to minimize the average waiting time across all vehicles:

$$\min \overline{W} = \min \frac{1}{N} \sum_{i=1}^{N} W_i \tag{12}$$

subject to the following constraints:

- **Maximum waiting time constraint**: No vehicle should wait longer than a predefined threshold:
$$W_i \le W_{\text{bound}}^{\max} \quad \forall i \in \{1, \ldots, N\} \tag{13}$$
- **Fairness constraint**: The system must maintain a minimum equity level across directions:
$$J \ge J_{\min} \tag{14}$$

Here, $W_{\text{bound}}^{\max}$ is an upper bound on the maximum acceptable waiting time, and $J_{\min}$ is a lower bound on the acceptable fairness index. This formulation prioritizes delay minimization while enforcing fairness and bounded service guarantees across all approaches.

This objective balances system-wide efficiency with individual fairness guarantees, providing a comprehensive framework for evaluating our proposed control strategies. The next section details the consensus algorithms used within this formulation.

III. Main Results

A. Key Findings

Simulation analysis demonstrates that the Average Consensus[12] algorithm with Extended Chain topology provides superior performance gains for intersection management, reducing average waiting time by 57.1% compared to the baseline approach while maintaining competitive throughput and fairness indices. These findings validate the efficacy of our two-layer architecture and suggest specific implementation guidelines for operational deployments.

In the subsequent sections, we first elucidate the fundamental challenges and our architectural solution, then present comprehensive experimental results comparing consensus-topology combinations across multiple performance metrics.

B. Challenges and Solution Approach

The primary challenge in traffic intersection management is optimizing multiple competing objectives (delay minimization, maximum wait constraints, fairness) under strict computational and communication constraints. Centralized approaches become computationally infeasible as vehicle density increases due to:

- Communication congestion when all vehicles report state information to a central controller
- Quadratic computational complexity scaling with increasing vehicle count
- Limited real-time responsiveness in high-density scenarios

Our primary contribution is a scalable two-layer architecture where:

1) **Distributed Consensus Layer**: Vehicles exchange information with neighbors according to a defined topology, aggregating information through distributed consensus protocols requiring only local communication.
2) **Adaptive Controller Layer**: The controller receives aggregated information from the consensus layer, executing phase selection and timing calculations with constant-time complexity regardless of vehicle count.

This hybrid architecture resolves the tension between scalability and optimality by maintaining a bounded communication load while still providing the adaptive controller with sufficiently rich information to make near-optimal signal timing decisions.

C. System Flow Overview

Figure 4,shows main simulation flow, where vehicles generate observations, participate in consensus, and forward summarized data to the controller for signal updates and vehicle movement. On the right side, a parallel path handles observation logging and performance metric recording, enabling post-simulation analysis without interfering with the control loop.

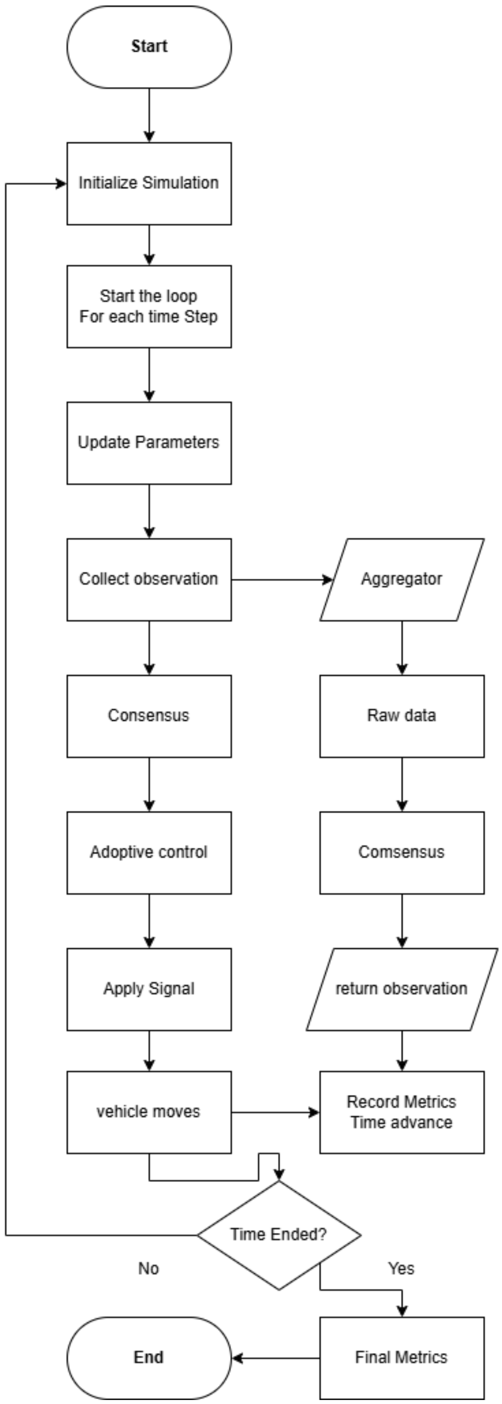

Fig. 4: Architecture-level system flow.

D. Controller Logic Flow

The information flow in Figure 5 illustrates how the adaptive controller governs traffic signal operations based on real-time input from the consensus layer. Using summarized data such as queue lengths and delays, the controller evaluates movement priorities, selects a compatible phase, and assigns an adaptive green time that reflects current traffic conditions.

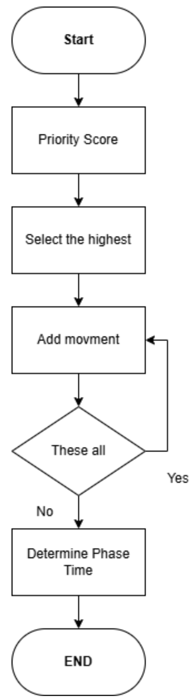

Fig. 5: Signal control logic

The consensus layer supports four algorithmic variants, each offering different trade-offs between accuracy and communication cost.
(see Section II :Problem-Formulation for formal definitions):

- **Global Information**: Idealized baseline assuming perfect connectivity and full state knowledge.
- **Max-Consensus (FloodMax)**: Distributes maximum values across the network using a flooding mechanism.[13]
- **Event-Triggered Consensus**: Minimizes communication by transmitting only when state changes exceed predefined thresholds.
- **Average Consensus with Front Priority**: Assigns greater influence to vehicles closest to the intersection to improve responsiveness.

Network topologies evaluated (ssee Section II for further details):

- **Centralized**: All vehicles communicate bidirectionally with controller and each other
- **Chain**: Vehicles communicate only with adjacent neighbors in the same lane
- **Extended Chain**: Front vehicles at intersection communicate directly across approaches
- **Chain + Front-Priority**: Standard chain with elevated weighting for front vehicles

E. Consensus-Topology Comparison Analysis

We conducted a comprehensive experimental evaluation of all consensus-topology combinations, with each configuration subjected to 100 independent simulation episodes of 3600 seconds duration. Identical traffic generation patterns (using fixed random seeds) were applied across all configurations to ensure comparative validity.

TABLE I: Statistical Comparison vs. Baseline (Global Information - Centralized)

Configuration	Avg Wait Diff	p-value	% Improv.
Avg Consensus - Extended Chain	7.942	< 0.0001	57.12%
Avg Consensus - Centralized	6.729	< 0.0001	48.40%
Event-Triggered - Chain + FP	0.533	< 0.0001	3.83%
Event-Triggered - Extended Chain	0.340	0.0007	2.45%
Max-Consensus - Chain	0.017	0.8404	0.12%
Avg Consensus - Chain	-0.135	0.1054	-0.97%
Max-Consensus - Extended Chain	-3.300	< 0.0001	-23.73%
Max-Consensus - Centralized	-8.192	< 0.0001	-58.91%

1) Comprehensive Performance Results: Table II presents the quantitative results of our multi-run analysis, displaying mean and standard deviation for each performance metric across all evaluated consensus-topology combinations.

As demonstrated in Table II, performance varies significantly across configurations. The optimal configurations for each metric are as follows:

- **Average Waiting Time**: Average Consensus with Extended Chain yields the minimum average waiting time (6.0 ± 0.2 s), representing a 57.1% reduction compared to the baseline configuration.
- **Maximum Waiting Time**: Average Consensus with Extended Chain similarly provides the best worst-case performance with a maximum waiting time of 55.22 ± 7.00 seconds, constituting a 53.3% reduction relative to baseline.
- **Throughput**: Max-Consensus with Centralized topology generates the highest throughput (3627 ± 703 vehicles per hour), an 8.9% improvement over baseline.
- **Fairness**: Max-Consensus with Centralized topology exhibits the highest Jain's fairness index (0.5470 ± 0.1158), a 5.3% improvement over baseline.

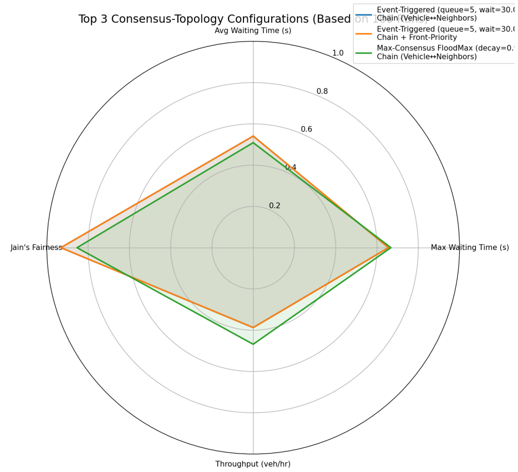

Fig. 6: Radar chart comparing performance metrics of top-performing configurations

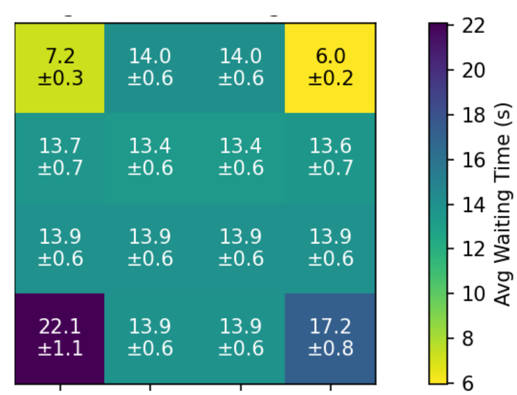

Fig. 7: Box-plot distribution of average waiting times across consensus-topology configurations

TABLE II: Multi-Run Consensus-Topology Comparison (100 Episodes, 3600s Each)

Consensus Algorithm & Topology	Avg. Wait (s) Mean ± Std	Max Wait (s) Mean ± Std	Throughput (veh/hr) Mean ± Std	Fairness Mean ± Std
Global Information - Centralized	13.90 ± 0.64	118.25 ± 21.11	3332 ± 479	0.5193 ± 0.1456
Global Information - Chain	13.90 ± 0.64	118.25 ± 21.11	3332 ± 479	0.5193 ± 0.1456
Global Information - Extended Chain	13.90 ± 0.64	118.25 ± 21.11	3332 ± 479	0.5193 ± 0.1456
Global Information - Chain + Front-Priority	13.90 ± 0.64	118.25 ± 21.11	3332 ± 479	0.5193 ± 0.1456
Max-Consensus - Centralized	22.10 ± 1.09	186.39 ± 30.10	$\mathbf{3627 \pm 703}$	$\mathbf{0.5470 \pm 0.1158}$
Max-Consensus - Chain	13.89 ± 0.61	98.86 ± 17.02	3395 ± 489	0.5376 ± 0.1375
Max-Consensus - Extended Chain	17.20 ± 0.82	127.13 ± 19.68	3487 ± 526	0.5445 ± 0.1201
Max-Consensus - Chain + Front-Priority	13.89 ± 0.61	98.86 ± 17.02	3395 ± 489	0.5376 ± 0.1375
Event-Triggered - Centralized	13.66 ± 0.66	109.18 ± 19.00	3368 ± 580	0.5218 ± 0.1259
Event-Triggered - Chain	13.37 ± 0.57	100.38 ± 18.15	3360 ± 452	0.5426 ± 0.1340
Event-Triggered - Extended Chain	13.56 ± 0.72	109.58 ± 20.17	3369 ± 447	0.5229 ± 0.1361
Event-Triggered - Chain + Front-Priority	13.37 ± 0.57	100.38 ± 18.15	3360 ± 452	0.5426 ± 0.1340
Average Consensus - Centralized	7.18 ± 0.28	86.62 ± 17.37	3211 ± 399	0.4901 ± 0.1362
Average Consensus - Chain	14.04 ± 0.59	105.61 ± 19.60	3424 ± 479	0.5274 ± 0.1366
Average Consensus - Extended Chain	$\mathbf{5.96 \pm 0.19}$	$\mathbf{55.22 \pm 6.95}$	3191 ± 325	0.4823 ± 0.1695
Average Consensus - Chain + Front-Priority	14.04 ± 0.59	105.61 ± 19.60	3424 ± 479	0.5274 ± 0.1366

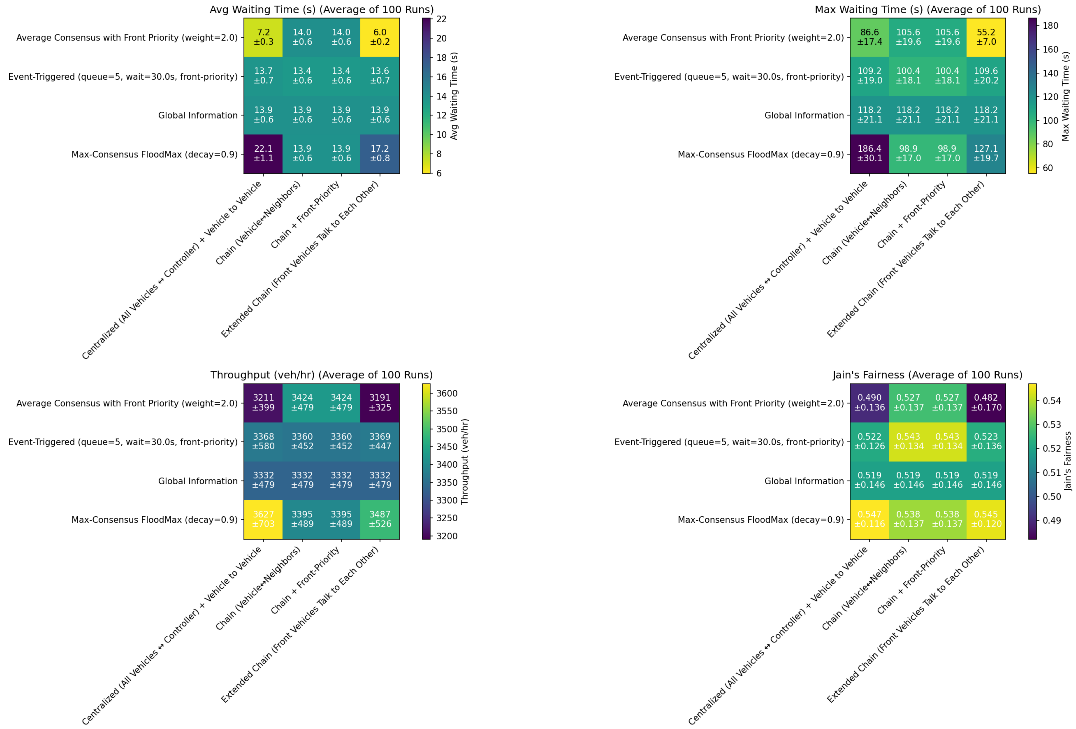

Fig. 8: Heatmap visualization of performance metrics across consensus-topology configurations

2) Statistical Significance Analysis: We conducted paired statistical tests to evaluate each configuration against the baseline (Global Information with Centralized topology). The results in Table II confirm that the observed performance differences are statistically significant in most configurations.

The performance distributions across all simulation runs are visualized in Figure 8, highlighting not only the superior mean performance but also the remarkably consistent behavior of the Average Consensus with Extended Chain configuration, as evidenced by its minimal variance.

3) Performance Trade-offs: Our analysis reveals fundamental trade-offs between performance metrics. Figure 8 provides an integrated visualization of all metrics across consensus-topology combinations.

F. Dominance of Front-Priority Extended Chain Consensus

Our proposed configuration—Average Consensus combined with an Extended Chain topology and front-priority logic—consistently outperforms alternative approaches across critical delay metrics. Specifically, it reduces average waiting time by 57.1% and maximum waiting time by 53.3% compared to the centralized global-information baseline. Notably, it also exceeds the performance of fully connected Average Consensus in both mean delay (5.96 s vs. 7.18 s) and delay consistency (± 0.19 s vs. ± 0.28 s). These results demonstrate that strategically structured partial connectivity, when combined with spatially-aware consensus algorithms, can exceed the performance of full-information architectures while maintaining bounded communication overhead. Although the configuration yields slightly lower throughput and fairness indices, it effectively prevents service starvation and maintains delay equity across directions, making it particularly suitable for delay-sensitive urban intersections.

G. Key Findings and Design Implications

Our comprehensive analysis yields several critical insights with significant implications for decentralized traffic management system design:

1) **Structured Partial Connectivity Superiority**: Our findings challenge the assumption that full state observability is always preferable, demonstrating that spatially structured partial connectivity can yield superior outcomes. This confirms that topology design is more consequential than complete information when paired with appropriate consensus mechanisms.
2) **Front-Vehicle Communication Value**: The Extended Chain topology, enabling direct communication between front vehicles at each approach, provides significant benefits when paired with Average Consensus. This targeted communication pattern delivers remarkable performance improvements with minimal overhead, creating a direct information pathway between approaches.
3) **Delay-Throughput Trade-off**: While Max-Consensus with Centralized topology achieves the highest throughput (+8.9%), it does so at the expense of significantly increased waiting times (+58.9%). In contrast, our method prioritizes delay reduction while maintaining acceptable throughput, representing an intentional design optimization for urban scenarios where waiting time minimization is critical.
4) **Variance Minimization**: Average Consensus with Extended Chain demonstrates exceptionally low variability

in performance (± 0.19 s), indicating robust behavior across diverse traffic conditions. This consistency is particularly valuable for operational deployment where predictable performance is essential.

5) **Bounded Communication Complexity**: Our system maintains constant communication complexity regardless of vehicle count, whereas centralized approaches scale poorly. This ensures our approach remains computationally feasible even in high-density traffic scenarios.

H. Fairness Analysis and Interpretation

It is important to note that perfect fairness is theoretically unattainable in intersection control due to fundamental asymmetries in the conflict graph. Right-turn movements have fewer conflicts and can typically proceed more frequently than left-turn movements, which face more restrictions. This structural imbalance creates an unavoidable trade-off: enforcing perfect fairness (index approaching 1.0) would necessitate artificially delaying non-conflicted movements, significantly increasing overall waiting times.

Our approach optimizes this trade-off by ensuring no movement experiences starvation (through the maximum waiting time component β) while still prioritizing overall system efficiency. The relatively consistent fairness indices across different consensus algorithms suggest that fairness characteristics are primarily determined by the controller logic rather than the information distribution mechanism.

I. Analysis of Average Consensus with Extended Chain

The significant performance improvements observed with Average Consensus with Extended Chain topology (57.1% reduction in waiting time) can be attributed to several key mechanisms:

- **Balanced Information Aggregation**: Unlike Max-Consensus which propagates only extreme values, Average Consensus incorporates the state of all vehicles, providing a more comprehensive representation of traffic conditions without bias toward the most congested approaches.
- **Extended Chain Synergy**: The cross-communication between front vehicles creates a direct information pathway in the network, allowing vehicles at different approaches to exchange information directly. This addresses a fundamental limitation of standard Chain topologies where information must traverse the entire queue to reach other approaches.
- **Spatial Relevance**: The Extended Chain naturally prioritizes information from vehicles closer to the intersection—precisely the vehicles with highest service priority—without requiring explicit weighting schemes. This enables more delay-sensitive decisions without increasing communication overhead.
- **Convergence Stability**: The averaging process creates more gradual transitions in control decisions compared to max-based approaches, preventing oscillations and reducing the variance in waiting times.
- **Partial Observability Sufficiency**: Our findings confirm that full system observability is not necessary for optimal performance. The structured partial connectivity of the Extended Chain provides precisely the critical information required for effective control decisions.

Notably, the superior performance of our method compared to Average Consensus with Centralized topology (5.96 s vs. 7.18 s) demonstrates that indiscriminate information aggregation is suboptimal. The fully connected topology may introduce extraneous information from distant vehicles that is less relevant to immediate control decisions, whereas the Extended Chain inherently filters information based on spatial proximity to the intersection.

J. Comparative Performance of Alternative Approaches

1) Max-Consensus Performance Analysis: The reduced performance of Max-Consensus with Centralized topology (58.9% increase in waiting time) despite achieving the highest throughput reveals an important limitation:

- **Extreme Value Sensitivity**: Max-Consensus inherently prioritizes the most congested approaches, potentially leading to resource monopolization where a single congested approach receives disproportionate service allocation.
- **Throughput-Delay Trade-off**: The higher throughput achieved by this configuration occurs at the expense of serving predominantly the heaviest flows, neglecting less-congested approaches and creating extended delays for vehicles in secondary flows.
- **Topology Amplification**: The Centralized topology exacerbates this issue by ensuring all vehicles are aware of the global maximum, whereas Chain topologies inherently attenuate extreme values through hop-by-hop propagation.

2) Event-Triggered Consensus Evaluation: Event-Triggered consensus demonstrates consistently moderate performance across all topologies, with minimal variation between different communication structures:

- **Adaptive Communication Frequency**: By transmitting only when significant changes occur, Event-Triggered consensus dynamically adjusts its communication intensity based on traffic dynamics.
- **Topology Independence**: The reduced sensitivity to topology configuration suggests that selective communication timing is more influential than communication structure for this algorithm class.
- **Communication-Performance Balance**: Event-Triggered represents an effective balance between performance improvement (3.8% over baseline) and communication efficiency, making it suitable for bandwidth-constrained deployment scenarios.

These insights provide valuable guidance for system designers, emphasizing that the selection of consensus algorithm and communication topology should be optimized based on specific deployment constraints and performance objectives.

K. Practical Implementation Guidelines

Based on our findings, we recommend the following implementation strategies for decentralized traffic management systems:

- **For delay minimization**, implement Average Consensus with Extended Chain topology, particularly in urban centers where waiting time reduction is the primary objective.
- **For throughput maximization**, deploy Max-Consensus with Centralized topology in high-volume corridors where capacity is the primary constraint, with appropriate consideration of the delay implications.
- **For balanced performance**, implement Event-Triggered with Chain topology, which provides moderate improvements across all metrics with reduced communication requirements.
- **For communication-constrained environments**, utilize Average Consensus with Centralized topology, which delivers significant delay reduction (48.4%) without requiring vehicle-to-vehicle communication infrastructure.

L. Communication Efficiency Analysis

Quantifying the communication overhead of various consensus algorithms is essential for real-world deployment feasibility, particularly in bandwidth-constrained environments. We formalize the communication complexity for each consensus protocol.

Let n be the number of agents (vehicles), $G = (V, E)$ the communication graph, $|E|$ its number of edges, $\bar{d} = 2|E|/n$ the average degree, and D its diameter.

1) Global Information (Ideal Baseline): Update (one round):

$$x_{\text{glob}} \;=\; \frac{1}{n}\sum_{i=1}^{n} x_i, \quad x_i \leftarrow x_{\text{glob}} \;\forall i. \tag{15}$$

Communication complexity:

- Each agent $\rightarrow$ controller: n messages.
- Controller $\rightarrow$ all agents: n messages.
- Total: $2n = O(n)$.
- Convergence in one round.

2) FloodMax (Max-Consensus): Update (iteration $k \rightarrow k+1$):

$$x_i^{k+1} = \max\left(x_i^k,\ \max_{j\in\mathcal{N}_i} x_j^k\right). \tag{16}$$

Communication complexity:

- Per iteration: each edge carries one max-value message $\Rightarrow |E|$ messages.
- Convergence in maximum D iterations.
- Total worst-case: $O(D\,|E|) = O(D\,n\,\bar{d})$.

3) Event-Triggered Consensus (Average-Type): Underlying update when agent i transmits at time t:

$$x_i(t^+) = \alpha\, x_i(t) + (1-\alpha)\sum_{j\in\mathcal{N}_i} w_{ij}\, x_j(t), \quad w_{ij} = \tfrac{1}{|\mathcal{N}_i|}\,. \tag{17}$$

Transmission rule (agent i only sends if any trigger holds):

$$\text{transmit if } q_i \geq Q_{\text{th}} \,\vee\, w_i^{\max} \geq W_{\text{th}} \,\vee\, t - t_i^{\text{last}} \geq T_{\text{th}}. \tag{18}$$

Communication complexity:

- Let each agent trigger on average M times.
- Each trigger produces up to $|\mathcal{N}_i| \approx \bar{d}$ messages.
- Total messages: $O(M\,n\,\bar{d})$.
- In worst-case $M \leq K$ (same as periodic consensus), so $O(K\,n\,\bar{d})$.

4) Front-Priority Weighted Average Consensus: Update (iteration $k \rightarrow k+1$):

$$x_i^{k+1} = \alpha_{\text{self}}\, x_i^k + (1-\alpha_{\text{self}})\sum_{j\in\mathcal{N}_i} w_{ij}\, x_j^k, \tag{19}$$

where

$$w_{ij} = \frac{1+\lambda\,\frac{|\text{front}_j|}{K}}{\sum_{\ell\in\mathcal{N}_i}\left(1+\lambda\,\frac{|\text{front}_\ell|}{K}\right)}, \quad \sum_j w_{ij} = 1. \tag{20}$$

Communication complexity:

- Per iteration: $|E|$ messages (each agent communicates with its neighbors).
- Convergence in K iterations (mixing-time dependent).
- Total: $O(K\,|E|) = O(K\,n\,\bar{d})$.

5) Communication-Performance Trade-offs: Table II presents a comparative analysis of communication overhead versus performance gains across consensus-topology configurations. We report the total messages exchanged per hour, normalized messages per vehicle per hour, and a derived efficiency metric: the number of messages required to achieve a 1% reduction in average waiting time relative to the baseline.

The results highlight a critical trade-off: while Average Consensus with Extended Chain topology achieves the maximum delay reduction (57.1%), it requires moderate communication overhead. Event-Triggered consensus on a Chain topology achieves a 3.8% delay reduction with minimal communication, requiring only 159.5 messages per hour—making it the most communication-efficient configuration in our evaluation. These findings emphasize the importance of selecting the appropriate consensus algorithm not only based on performance but also on communication constraints.

Event-Triggered consensus achieves the optimal balance between communication efficiency and performance, requiring only 6.9% of the messages needed by Average Consensus with Extended Chain while delivering 6.7% of the performance improvement. This makes Event-Triggered particularly suitable for bandwidth-constrained environments with limited communication resources.

M. Communication Efficiency at Scale

Our analysis reveals the critical impact of communication topology on scalability in high-density traffic scenarios. While Average Consensus with Extended Chain provides optimal delay performance, its communication cost scales linearly with vehicle count. Figure 8 compares the scaling behavior of different consensus-topology combinations as traffic density increases.

The fundamental advantage of our approach is that the controller communication load remains constant regardless of

TABLE III: Communication Costs and Efficiency Metrics (100 Replications, 1-Hour Runs)

Algorithm & Topology	Msgs/Vehicle/Hr	Total Msgs/Hr	Msgs per % Improv.
Global Information – Chain	809.0	809.0	–
FloodMax – Centralized	11564.0	11564.0	1223.4
FloodMax – Chain	704.0	704.0	4.9
FloodMax – Extended Chain	2236.0	2236.0	34.3
Event-Triggered – Centralized	2417.5	2417.5	24.9
Event-Triggered – Chain	159.5	159.5	4.9
Event-Triggered – Extended Chain	364.5	364.5	6.0
Average Consensus – Centralized	5944.0	5944.0	122.3
Average Consensus – Chain	1082.0	1082.0	–
Average Consensus – Extended Chain	2314.0	2314.0	42.4

the number of vehicles in the system. Only front vehicles communicate directly with the controller, creating an effective bottleneck protection mechanism that traditional centralized systems lack. This constant-time controller interaction is essential for real-world deployments where computational resources at the intersection are limited.

N. The Critical Role of Front-Vehicle Information Exchange

The significant performance improvements of our proposed method can be largely attributed to the Extended Chain topology's capability to facilitate direct communication between vehicles at the front of each approach. This direct information pathway provides several advantages:

- **Reduced Information Latency**: Front vehicles can immediately share state information with vehicles from other approaches, eliminating multi-hop propagation delays.
- **Conflict Resolution**: Direct communication between potential conflict points enables more responsive decision-making regarding movement prioritization.
- **Self-Adjusting Priorities**: The natural weighting in the Extended Chain topology gives higher influence to vehicles closest to the intersection, those with the most urgent service requirements.
- **Information Relevance Filtering**: By structuring communication primarily along chains with selective cross-connections, irrelevant information from distant vehicles is effectively filtered.

This structured partial connectivity creates a virtual ”front-zone awareness,” aligning control priority with spatial proximity to the intersection. The proximity of a vehicle to the intersection proportionally influences control decisions—an intrinsic priority scheme inherent in the topology design itself.

O. Comparative System Stability Analysis

A significant advantage of our Average Consensus with Extended Chain approach is its exceptional stability in performance across diverse traffic conditions. As shown in Table II, our method not only achieves the minimum average waiting time but also demonstrates the lowest standard deviation (± 0.19 s), indicating highly consistent performance.

This consistency is particularly valuable for operational deployments, where predictable system behavior is essential for driver experience and system reliability. The adaptive nature of our approach allows it to maintain consistent performance even under varying traffic densities and arrival patterns.

P. Real-World Implementation Considerations

While our simulation results demonstrate significant potential benefits from distributed consensus approaches, several practical considerations must be addressed for implementation:

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1) Communication Reliability and Partial Connectivity: Our current simulation assumes perfect communication without latency, packet loss, or interference. In practice, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication face several challenges:

- **Partial Connectivity**: During transition periods, only a subset of vehicles will be equipped with communication capabilities. The architecture would need to incorporate detection systems (cameras, inductive loops) to account for non-connected vehicles.
- **Communication Reliability**: V2V communication using DSRC or C-V2X standards faces challenges from signal attenuation, interference, and packet collisions. Robust consensus algorithms should maintain performance under message loss and transmission delays.
- **Bandwidth Constraints**: Available bandwidth may constrain the frequency and packet size of messages, particularly in dense traffic scenarios. This reinforces the importance of communication-efficient algorithms like Event-Triggered consensus.

2) Hardware and Software Requirements: The distributed architecture requires specific hardware and software capabilities:

- **Vehicle Requirements**: Connected vehicles need onboard units (OBUs) with wireless transceivers, positioning systems, and computational capabilities for consensus algorithm execution.
- **Infrastructure Requirements**: Intersections need roadside units (RSUs) with sufficient computational capacity to execute the adaptive controller, local storage for traffic patterns, and reliable power supply.
- **Software Architecture**: A modular software implementation would enable incremental deployment and updates,

with defined interfaces between sensing, consensus, control, and monitoring modules.

3) Transition Strategy: Practical implementation would require a phased deployment approach:

- **Initial Deployment**: Install infrastructure at high-priority intersections with significant congestion, while maintaining traditional signal control as a fallback mechanism.
- **Evaluation Period**: Collect data on performance improvements and system reliability before extending to additional intersections.
- **Gradual Expansion**: Implement across coordinated corridors to maximize network effects and develop adaptive coordination mechanisms between adjacent intersections.

These practical considerations highlight important directions for future work, including developing robust algorithms that maintain performance under realistic communication constraints and partial connectivity scenarios.

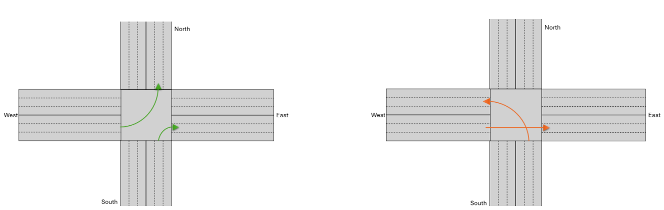
IV. Simulation

A. Purpose

The simulation provides a controlled, repeatable platform to test our decentralized traffic control architecture under various consensus algorithms and communication topologies. By abstracting away low-level vehicle dynamics, we focus on information exchange patterns, decision logic effectiveness, and system-level performance metrics to assess the behavior of our proposed approach under varied communication constraints. This environment allows us to systematically evaluate how different communication constraints affect traffic flow efficiency.

B. Simulation Environment

1) Intersection Geometry: Our simulation models a standard four-way intersection with dedicated lanes for left turns, through traffic, and right turns from each direction (North, South, East, West). We adopt a FIFO queuing abstraction for each lane, consistent with established traffic signal simulation practices [1]. Vehicles are discharged at fixed rates of 1 vehicle per second for left turns and 2 vehicles per second for through and right turns, which aligns with deterministic traffic models that abstract away vehicle-level dynamics while capturing the essential service rate differences between movement types.



(a) Non-conflicting movements (b) Conflicting movements

Fig. 9: Intersection movement patterns under two conditions:
(A) safe, non-conflicting trajectories;
(B) conflicting trajectories requiring additional control.

2) Traffic Generation: We selected an arrival rate of 0.2 vehicles per second per direction (equivalent to 720 vehicles/hour per approach, totaling 2880 vehicles/hour across all four approaches) to model a moderately congested urban intersection. This setting aligns with reported peak-hour flow capacities observed in real-world traffic systems, which typically range from 1800 to 2400 vehicles per hour per intersection [1]. Our arrival patterns follow a Bernoulli process, consistent with prior discrete-event traffic simulations [14].

For each vehicle arrival, movement probabilities are set to 20% for left turns, 60% for through movements, and 20% for right turns, representing typical urban traffic distribution patterns. These values create sufficient diversity in lane utilization to test the adaptive capabilities of our control approaches.

3) Conflict Graph: To determine which movements can safely occur simultaneously, we maintain a conflict graph that encodes the geometric constraints of the intersection. Each directed edge in this graph represents a potential collision between two movements. For example, a northbound left turn conflicts with a southbound through movement. The conflict graph is queried during each phase selection cycle to ensure that all activated movements are non-conflicting, enabling safe parallel flow within the adaptive control logic.

C. Simulated Communication Topologies

Our simulation evaluates four distinct vehicle-to-vehicle and vehicle-to-infrastructure communication configurations:

1) **Centralized (Global Information):** All vehicles communicate directly with the controller and with each other, representing an idealized V2I scenario with perfect information sharing.
2) **Chain:** Vehicles only communicate with adjacent vehicles in the same lane, with only the front vehicle in each lane connecting to the controller. This models limited-range communications where direct controller access is position-dependent.
3) **Chain + Front-Priority:** Extends the Chain topology by assigning higher weights to information coming from vehicles closer to the intersection, reflecting the intuition that front vehicles' states more urgently affect control decisions.
4) **Extended Chain:** Further enhances the Chain + Front-Priority model by allowing front vehicles from different approaches to communicate with each other, creating a front-line information exchange network.

These configurations reflect practical limitations in connected vehicle communication systems.

D. Control Strategies Under Evaluation

We simulate four distinct control strategies to evaluate different approaches to distributed information aggregation. Formal definitions and theoretical motivations for each consensus algorithm are presented in Section 3.

1) Global Information: Serves as our baseline, using perfect information about all vehicles without any consensus needed. While unrealistic in practice, it provides an upper bound on performance against which other approaches can be measured.

2) Max-Consensus (FloodMax): Simulates a protocol where maximum values (queue lengths, waiting times) propagate across agents according to communication topology constraints. We use a decay factor of 0.9 to gradually discount outdated information across iterations.

3) Average Consensus with Front Priority: Models a weighted averaging scheme where vehicles closer to the intersection have greater influence on the final state estimation. This simulates realistic urgency in vehicle-based communication where front vehicles' information is more time-sensitive.

4) Event-Triggered Consensus: Simulates a bandwidth-efficient approach where vehicles only share updates when significant changes occur in local state. We configure this with three thresholds:

- Queue threshold $Q_{th} = 5$ vehicles
- Wait threshold $W_{th} = 30$ seconds
- Time threshold $T_{th} = 10$ seconds

These values are consistent with event-triggered communication protocols explored in traffic control literature [14] and represent practical bandwidth conservation strategies.

E. Adaptive Traffic Controller

The controller uses aggregated lane information from the consensus algorithms to make signal timing decisions. For each green phase, it:

1) Scores each potential movement based on queue length and waiting time:
$$S_{d,m} = \alpha \cdot Q_{d,m} + \beta \cdot W_{max,d,m} + \gamma \cdot W_{avg,d,m} \quad (21)$$
where $\alpha = 0.3$, $\beta = 0.2$, and $\gamma = 0.2$ are weights for queue length, maximum waiting time, and average waiting time, respectively. These weights were determined through parameter optimization to balance responsiveness to different traffic metrics.
2) Selects the highest-scoring movement and adds any non-conflicting movements that can run simultaneously.
3) Determines green phase duration based on queue sizes and waiting times, bounded between a minimum of 5 seconds and maximum of 45 seconds.

This approach adapts both phase selection and timing to current traffic conditions, prioritizing movements with the most congestion and longest delays.

F. Simulation Parameters

In our experiments, we use the following key simulation parameters:

- Simulation time step: 1.0 second
- Total simulation duration: 300 seconds per scenario
- k-front parameter for lane observation: 8 vehicles (defines how many front vehicles' information is tracked separately)
- Minimum green time: 5 seconds
- Maximum green time: 45 seconds
- Number of independent simulation runs per configuration: 10 (with different random seeds)

For selected configurations, we extended the simulation duration to 3600 seconds and ran 100 episodes to capture long-term behavioral trends. All configurations used identical random seeds within an episode to eliminate variability due to stochastic arrival patterns and enable fair, statistically sound comparisons. This determinism ensures that observed differences in outcome are attributable solely to algorithmic or topological variations. All simulation runs are reproducible using fixed seeds, and the experimental scripts are available upon request.

TABLE IV: Extended-horizon simulation protocol

Parameter	Value
Simulation horizon	3,600 seconds (1 hour)
Time step (Δt)	1 second
Number of replications	100 paired runs
Measurement window	Full [0, 3,600] seconds
Seed protocol	Identical Python/NumPy seeds per replication

G. Performance Metrics

We track several key performance metrics throughout the simulation to evaluate the effectiveness of the different consensus approaches:

1) Traffic Volume: We measure traffic volume as the number of vehicles passing through the intersection per hour. This aligns with standard traffic engineering definitions where volume is measured in vehicles per hour (veh/h) [1].

2) Queue Length: Average queue length is tracked as the sum of queue lengths over all approaching lanes, with smaller values indicating fewer waiting vehicles. This metric is widely used as an indicator of traffic congestion and control effectiveness [14], as it directly reflects the number of vehicles waiting to be served.

3) Waiting Time: Vehicle waiting time, defined as the difference between arrival and discharge times, serves as a proxy for travel duration through the intersection. This metric aligns with how intersection performance is evaluated in real-world studies [14]. We track both average and maximum waiting times to capture both overall efficiency and worst-case delays.

4) Communication Overhead: We measure the total number of messages exchanged between vehicles and the controller throughout the simulation to quantify communication costs. This metric is particularly important for evaluating the efficiency of event-triggered protocols compared to continuous information exchange systems.

V. Conclusion

Urban intersections are increasingly strained by growing vehicle volumes and the coexistence of heterogeneous traffic participants, including human-driven, connected, and automated vehicles. Traditional centralized traffic signal control systems often fall short in adapting to the dynamic demands of such environments, leading to inefficiencies and prolonged delays.

This study introduced a scalable two-layer architecture for intersection management, combining a distributed consensus layer with a centralized adaptive traffic light controller. By adopting structured communication topologies—such as the Extended Chain—and leveraging consensus algorithms, the system aggregates traffic data locally before transmitting compact summaries to the controller. This approach reduces communication overhead and computational burden while preserving real-time responsiveness.

Simulation experiments demonstrated that the Average Consensus algorithm, when paired with the Extended Chain topology, achieved substantial improvements: a 57.1% reduction in average waiting time and a 53.3% reduction in the worst-case delays. Notably, this configuration outperformed even fully connected centralized systems, indicating that partial but well-structured connectivity can offer superior control outcomes. Additionally, Event-Triggered Consensus strategies showed promise in bandwidth-limited settings, achieving significant delay reductions with minimal message exchange.

The architecture's modularity and low sensitivity to full CAV penetration make it suitable for gradual real-world deployment. By prioritizing vehicles nearest to the intersection, the system responds more effectively to immediate traffic conditions, ensuring fairness and preventing starvation of low-volume movements.

A. *Future Research Directions*

While the current framework operates under idealized communication assumptions, several avenues exist to enhance its robustness and applicability in real-world scenarios:

- **Heterogeneous Driver Behavior Modeling**: Future implementations should incorporate predictive modules capable of estimating the behavior of human drivers in mixed environments. Since human behavior is less predictable than that of automated or connected vehicles, integrating trajectory prediction models—potentially supported by camera-based detection or vehicle kinematics—will be essential for improving control accuracy and responsiveness.
- **Partial Information and Communication Delay Analysis**: The current study assumes complete and instantaneous data exchange. Future work should simulate scenarios with varying levels of information availability (e.g., 80%, 70%, 60% observability) and communication delays. This analysis will help determine the minimum required penetration of connected vehicles or information fidelity needed to achieve performance gains over traditional fixed-cycle signal control. Identifying a "break-even" threshold will be critical for planning staged deployments in partially connected environments.
- **Smart Corridor and Multi-Intersection Integration**: Extending the architecture to manage not just individual intersections but entire corridors will further enhance throughput and reduce travel time. Coordinating multiple intersections using shared consensus data and predictive flow estimation could enable more holistic traffic optimization across city grids.
- **Adaptive Learning for Controller Tuning**: Incorporating machine learning models to dynamically adjust controller weights based on real-time traffic flow patterns, day-of-week variations, and historical data can further improve the system's adaptability and robustness.
- **Resilience under Uncertainty**: Developing versions of the consensus algorithms that can tolerate packet loss, variable latency, and adversarial conditions will be vital for deployment in realistic environments. Techniques from fault-tolerant distributed systems may be adapted to maintain system stability in degraded communication conditions.
- **Field Trials and Deployment Studies**: Finally, real-world pilot studies and hardware-in-the-loop simulations should be conducted to validate the system's effectiveness under actual traffic and communication conditions. These studies would inform deployment standards, safety benchmarks, and integration with smart city infrastructure.

This work provides a flexible and efficient foundation for the next generation of decentralized intersection control systems. By combining spatially aware communication topologies with lightweight consensus protocols, the proposed architecture delivers substantial performance improvements while maintaining operational simplicity. These results support a paradigm shift from rigid, centralized signal control to distributed, data-driven coordination—one that is more compatible with the evolving landscape of intelligent transportation systems.

REFERENCES

[1] M. Papageorgiou, C. Diakaki, V. Dinopoulou, A. Kotsialos, and Yibing Wang. Review of road traffic control strategies. *Proceedings of the IEEE*, 91(12):2043–2067, 2003.

[2] Jinjue Li, Chunhui Yu, Zilin Shen, Zicheng Su, and Wanjing Ma. A survey on urban traffic control under mixed traffic environment with connected automated vehicles. *Transportation Research Part C: Emerging Technologies*, 154:104258, 2023.

[3] Nishanth Venkatesh, Viet-Anh Le, Aditya Dave, and Andreas A. Malikopoulos. Connected and automated vehicles in mixed-traffic: Learning human driver behavior for effective on-ramp merging. In *2023 62nd IEEE Conference on Decision and Control (CDC)*, pages 92–97, 2023.

[4] Pin-Chun Chen, Xiangguo Liu, Chung-Wei Lin, Chao Huang, and Qi Zhu. Mixed-traffic intersection management utilizing connected and autonomous vehicles as traffic regulators. In *ASPDAC '23: Proceedings of the 28th Asia and South Pacific Design Automation Conference*. Association for Computing Machinery, 2023.

[5] Matine Hajyan and Amirhossein Nikoofard. Fuzzy control of autonomous vehicle at non-signalized intersection in mixed traffic flow. In *2022 9th Iranian Joint Congress on Fuzzy and Intelligent Systems (CFIS)*, pages 1–6, 2022.

[6] Zhihong Yao, Bin Zhao, Yuan Tengfei, Haoran Jiang, and Yangsheng Jiang. Reducing gasoline consumption in mixed connected automated vehicles environment: A joint optimization framework for traffic signals and vehicle trajectory. *Journal of Cleaner Production*, 265:121836, 2020.

[7] Yue Zhang and Christos G. Cassandras. Decentralized optimal control of connected automated vehicles at signal-free intersections including comfort-constrained turns and safety guarantees. *Automatica*, 109:108563, 2019.

[8] Faiza Gul, Adnan Mir, Imran Mir, Suleman Mir, Tauqeer Ul Islaam, Laith Abualigah, and Agostino Forestiero. A centralized strategy for multi-agent exploration. *IEEE Access*, 10:126871–126884, 2022.

[9] Francesco Smarra, Giovanni Domenico Di Girolamo, Vittorio De Iuliis, Achin Jain, Rahul Mangharam, and Alessandro D'Innocenzo. Data-driven switching modeling for mpc using regression trees and random forests. *Nonlinear Analysis: Hybrid Systems*, 36:100882, 2020.

[10] Ren Zhang and Marco Pavone. Control of robotic mobility-on-demand systems: A queueing-theoretical perspective. *The International Journal of Robotics Research*, 35(1–3):186–203, 2015.

[11] Hassan Jafarzadeh and Cody Fleming. Dmpc: A data-and model-driven approach to predictive control. *Automatica*, 131:109729, 2021.

[12] Lin Xiao, Stephen Boyd, and Seung-Jean Kim. Distributed average consensus with least-mean-square deviation. *Journal of Parallel and Distributed Computing*, 67(1):33–46, 2007.

[13] Franck Iutzeler, Philippe Ciblat, and Jérémie Jakubowicz. Analysis of max-consensus algorithms in wireless channels. *IEEE Transactions on Signal Processing*, 60(11):6103–6107, 2012.

[14] Lei Ding, Qing-Long Han, Xiaohua Ge, and Xian-Ming Zhang. An overview of recent advances in event-triggered consensus of multiagent systems. *IEEE Transactions on Cybernetics*, 48(4):1110–1123, 2018.