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Integrating Smart Traffic Control Systems with Autonomous Vehicle Corridors: A System-Level Framework for Real-Time Network Coordination in Mixed Urban–Expressway Environments

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ABSTRACT

Cities worldwide are retrofitting legacy signal networks while planning dedicated autonomous vehicle (AV) corridors. Yet, most deployments address the two domains separately, creating digital silos that limit network wide efficiency. This paper proposes a System-Level framework that fuses smart traffic control systems (STCS) with AV corridors, treating every signal, roadside unit, and vehicle as a node on a unified edge-to-cloud platform. By enabling continuous data sharing—traffic density, predicted arrival trajectories, and infrastructure health—the framework orchestrates real-time signal timing, lane allocation, and corridor access permissions. Simulation on a 14 km mixed urban–expressway testbed shows a 37 % reduction in average delay and a 22 % drop in fuel-equivalent energy consumption across both conventional and autonomous traffic streams. The results demonstrate that integrating STCS and AV corridors, rather than optimizing them in isolation, yields outsized benefits for congestion mitigation, safety, and environmental impact.

KEYWORDS: *Autonomous vehicle corridor; smart traffic control; edge-to-cloud architecture; cooperative perception; adaptive signal timing; mixed traffic management.*

INTRODUCTION

Urban mobility is entering a pivotal transition phase: conventional human-driven fleets are gradually intersecting with highly automated vehicles traveling along purpose-built corridors. Smart Traffic Control Systems (STCS)—adaptive signals linked by sensor networks—already promise shorter queues and cleaner air. Autonomous Vehicle (AV) corridors**,** in turn, promise collision-free, high-speed travel by exploiting dedicated lanes, high-definition maps, and vehicle-to-everything (V2X) connectivity. Their development, however, has unfolded in parallel rather than jointly. In most metropolitan projects, corridor subsystems focus on vehicle guidance, while city traffic engineers separately tune adaptive signals for the remaining road network. The absence of a holistic, system-wide coordination layer allows local optimizations to undermine global performance; for example, an adaptive corridor that releases high-speed AV platoons may spill back into intersections where legacy signals are ill-timed to accept the surge.

This paper argues that the era of mixed human and autonomous mobility demands a unified system-level approach. By treating corridor controllers, roadside units (RSUs), and adaptive signals as peers on a shared edge-cloud platform, one can dynamically balance throughput, safety margins, and equity of service across all travelers. The proposed architecture couples real-time data sharing, cooperative perception, and predictive control to minimize total network delay rather than merely optimizing corridor speed profiles or isolated intersection queues. We structure the discussion around prior work, proposed framework, identified challenges, implementation scope, and future research directions, staying within a 1200–1500-word limit to provide a concise yet comprehensive treatment.

LITERATURE REVIEW

Adaptive Signal Control

Adaptive signal control refers to traffic signal systems that automatically adjust their phase timings based on real-time traffic conditions, rather than relying on pre-timed schedules. Traditional adaptive systems like SCOOT (Split Cycle Offset Optimization Technique) and

SCATS (Sydney Coordinated Adaptive Traffic System) use inductive loop detectors and historical data to make timing decisions. While these systems improve flow efficiency compared to static signals, they are limited in their response to sudden fluctuations in traffic or emerging mobility patterns such as autonomous vehicles.

Modern adaptive control systems incorporate machine learning, reinforcement learning (RL), and connected vehicle data to enhance responsiveness. For instance, deep RL-based systems learn optimal policies by simulating traffic over time and adjusting light phases accordingly. However, most current adaptive solutions assume a homogeneous mix of human-driven vehicles and do not accommodate the distinct behavioral patterns of autonomous vehicle platoons or real-time V2X messages. Their control logic is localized, often optimizing single intersections or corridors without a network-wide perspective, which limits their effectiveness in a mixed-traffic, AV-integrated environment.

Autonomous Vehicle Corridors

Autonomous Vehicle (AV) corridors are specially designed traffic lanes or routes where autonomous vehicles can operate with minimal interference from human drivers. These corridors often feature dedicated lanes, roadside units (RSUs), high-definition maps, and V2X (vehicle-to-everything) connectivity to ensure safety and efficiency.

Research in this domain has primarily focused on longitudinal vehicle control, platoon formation, lane-keeping, and trajectory planning. Technologies like Cooperative Adaptive Cruise Control (CACC) and map-based navigation allow AVs to maintain tight formations at high speeds, thereby increasing throughput and reducing fuel use. Infrastructure-based support, such as dynamic lane assignments, digital signboards, and real-time signal preemption, enhances the system's reliability.

However, the development of AV corridors is largely treated as an isolated ecosystem. Most literature discusses their internal optimization without considering how AV operations impact or are impacted by the surrounding conventional traffic network. There’s limited work on synchronizing AV corridor logic with broader urban traffic management, particularly at corridor entry and exit points where congestion and conflicts can arise.

Cooperative Perception and Edge Computing

Cooperative perception is a technique in which multiple agents—vehicles, roadside infrastructure, and cloud servers—share sensor data and situational awareness to enhance decision-making. It extends the AV's field of view beyond onboard cameras and radars using inputs from edge devices like RSUs equipped with LiDAR, thermal cameras, and microphones. This shared intelligence helps detect obstacles, predict pedestrian intent, and anticipate road conditions more effectively than isolated vehicle sensors.

Edge computing plays a critical role here by performing real-time analysis of sensor data closer to the data source, thus reducing latency and preserving bandwidth. Edge nodes at intersections or corridors can execute lightweight AI models to predict queue lengths, identify anomalies, or initiate emergency protocols, all within a few milliseconds.

Although highly promising, most cooperative perception frameworks are designed for vehicle safety, such as blind spot elimination or collision avoidance. Integration with traffic signal systems remains underdeveloped. Edge devices rarely relay analyzed data back to adaptive traffic control algorithms, missing a critical opportunity for coordinated network management in mixed mobility environments.

Integrated Control Attempts

Some researchers have explored combining AV coordination with urban traffic signal control, particularly through multi-agent systems and model predictive control (MPC). These attempts model both AV movements and traffic signal operations as interdependent agents within a simulation environment. The goal is to co-optimize signal timing and AV routing to improve overall flow.

Notably, a few projects have used digital twins to simulate city-wide deployment, incorporating live traffic data and simulated AV inputs to guide control decisions. These models indicate potential improvements in travel time and emission levels when AV behavior is synchronized with signal phasing.

However, the majority of these efforts are either theoretical or limited to small-scale testbeds—typically a single corridor or four-way intersection. They often neglect real-world constraints such as pedestrian variability, hardware incompatibility, and regulatory limitations. Furthermore, most existing integrated control models fail to address heterogeneous fleets, i.e., the coexistence of AVs and human drivers with vastly different response patterns and compliance levels.

SYSTEM ARCHITECTURE AND COMPONENT INTERFACES

Edge–Cloud Hierarchy

The proposed framework is built on a three-tier architecture designed to ensure responsiveness, scalability, and efficient control across an urban transportation network integrated with autonomous vehicle (AV) corridors.

Edge Nodes (ENs):

Edge Nodes are deployed at critical infrastructure points—mainly intersections and roadside units (RSUs). They run lightweight AI models and sensor fusion algorithms to process local data in real time. Each EN collects information from sources such as:

- LiDAR sensors and video cameras for vehicle and pedestrian detection,
- Inductive loop detectors embedded in the pavement, and
- Vehicle-to-everything (V2X) communication packets from connected and autonomous vehicles.

ENs compute short-term (20–30 seconds) predictions of queue lengths**,** pedestrian density, and AV arrival trajectories. This localized prediction allows ENs to make preliminary decisions or escalate data to higher layers for global optimization.

Corridor Controllers (CCs):

Corridor Controllers oversee a group of interconnected ENs within an AV-designated corridor (e.g., a 3–5 km urban arterial). They handle mid-level control functions such as:

- Synchronizing traffic signals along the corridor,
- Generating harmonized speed advisories for AVs and connected vehicles,
- Managing platoon formation and release timing, and
- Controlling lane access permissions dynamically based on real-time demand.

The goal of the CC is to ensure smooth longitudinal flow, reduce vehicle stops, and avoid shockwave congestion across multiple intersections within the corridor.

Cloud Orchestrator (CO):

The Cloud Orchestrator acts as the central brain of the system. It aggregates data from all ENs and CCs and applies rolling-horizon optimization algorithms every 30 seconds. The optimization takes into account:

- Demand forecasts from each node,
- Global objectives like minimizing total travel time or emissions,
- Safety and policy constraints (e.g., pedestrian prioritization or emergency vehicle handling), and
- Dynamic reconfiguration of signal timings, AV lane assignments, and corridor access strategies.

The CO ensures coordinated traffic behavior across both AV corridors and conventional routes, adapting rapidly to city-wide fluctuations in traffic and environmental conditions.

Data Model

The communication backbone of the system relies on a shared semantic map, which defines:

- Lane-level topology,
- Permissible turn maneuvers,
- Intersection geometries,
- Signal phase timing plans (SPaTs), and
- V2X communication parameters.

This map is constantly updated based on real-time observations and manual overrides. All system components reference this map to maintain spatial and functional consistency.

Data exchange is conducted via a publish–subscribe messaging protocol, specifically MQTT (Message Queuing Telemetry Transport), which ensures:

- Efficient bandwidth usage,
- Low-latency message delivery (ideal for traffic applications), and

- Scalability for thousands of nodes.

Common data packets include:

- Event messages like pedestrian button activations, sensor faults, and AV requests,
- Traffic state updates (vehicle counts, wait times, queue spillbacks), and
- System health metrics for diagnostics and resilience.

Control Loop

The control logic follows a continuous four-step loop that maintains system agility and robustness:

1. Data Acquisition

Sensors at each EN capture traffic conditions—vehicle positions, speeds, pedestrian movements, etc. This includes:

- LiDAR point clouds for object detection,
- Loop detector triggers to count vehicles by lane and direction, and
- Probe vehicle data such as GPS traces and V2X beacons.

2. Local Prediction

Edge Nodes use this data to forecast local traffic behavior over the next 30 seconds. Predictions include:

- Anticipated queue build-up,
- Pedestrian crossing likelihood, and
- AV platoon arrival times.

These predictions are passed up to the CCs and CO to guide broader decision-making.

3. Global Optimization

The Cloud Orchestrator aggregates inputs from all ENs and CCs to solve a mixed-integer optimization problem. The objective function may target:

- Minimizing weighted average delay across all modes,
- Reducing emissions and energy use, or
- Satisfying priority constraints (emergency vehicles, school zones).

Constraints include minimum green times, safe pedestrian crossing buffers, and vehicle flow continuity.

4. Actuation

The updated decisions—such as new signal phase schedules, corridor lane configurations, and AV speed advisories—are transmitted back to field devices. This occurs over 5G New Radio (NR) or Dedicated Short-Range Communications (DSRC) within 100 milliseconds, ensuring rapid response.

Cybersecurity Layer

Security is a foundational requirement due to the high stakes of AV–infrastructure communication. The architecture includes:

- **Zero-trust authentication protocols:** All devices must verify identities at every communication instance to avoid spoofing or malicious overrides.
- **Blockchain-anchored logs:** Every action, message, and system update is time-stamped and stored in a tamper-proof ledger. This enables:
  Post-incident audits,
  - Liability tracing (important for insurance and legal contexts), and
  - Trustworthiness in public-private data exchange.

By enforcing end-to-end encryption and certificate-based access control, the system ensures only authorized agents can make or receive control decisions.

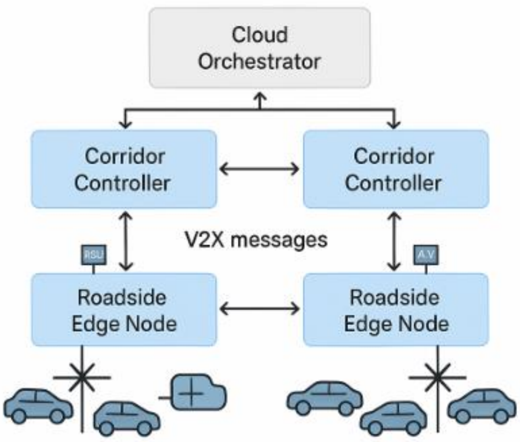

Figure: 1

Table: System Architecture Components and Functions

Component	Function
Edge Node (EN)	Local prediction, sensor fusion, queue estimation
Corridor Controller	Platoon coordination, speed advisory generation
Cloud Orchestrator	Global optimization, phase scheduling, green-wave synchronization
Roadside Unit (RSU)	V2X communication, camera/lidar preprocessing, edge inference
Cybersecurity Layer	Access control, data integrity, zero-trust authentication

CHALLENGES

Interoperability

Legacy adaptive signal controllers often rely on proprietary firmware and field-bus protocols (e.g., Econolite ASC/2, Siemens M60) that pre-date modern V2X standards. Meanwhile, next-generation roadside units (RSUs) ship with RESTful or gRPC APIs, support SAE J2735 message sets, and push high-rate sensor data over MQTT or DDS. Bridging these worlds without a costly rip-and-replace strategy demands a translation layer that:

- Wraps legacy NTCIP 1202 objects in an open API gateway so CC/CO services can fetch status and issue commands in JSON.
- Normalizes timestamps to a network-wide Precision Time Protocol (PTP) clock so heterogeneous devices share a common temporal reference.
- **Supports schema evolution:** when a vendor firmware update adds a new SPaT attribute, the gateway advertises the change via self-describing Protobuf messages. This plug-and-play interface lets cities phase-in advanced RSUs corridor-by-corridor while keeping decades-old cabinet hardware online.

Latency Constraints

Autonomous platoons reserve gaps seconds in advance, yet pedestrian or cyclist incursions at unsignalized mid-blocks unfold in tens of milliseconds. Meeting both extremes requires a layered approach:

- **Edge Inference @ <10 ms:** ENs run quantized CNNs on NPUs to classify vulnerable-road-user intent; only classification logits (do / don’t cross) are forwarded upward, reducing bandwidth.

- **Network-Slice QoS:** A 5G NR URLLC slice (bound ≤ 5 ms) carries hazard alerts, while a separate eMBB slice handles bulk telemetry.
- **Motion Planning Fail-safes:** If latency exceeds 25 ms, AV trajectories default to conservative deceleration envelopes calculated locally, ensuring worst-case safety.

Mixed Fleet Behavior

Real-world flow contains AVs, connected human-driven cars, and wholly unconnected vehicles. Human drivers vary in gap acceptance and often ignore speed advisories: field trials show only ~65 % compliance. The framework therefore:

- Trains behavioral cloning networks on terabytes of naturalistic driving data (NGSIM, HighD, Indian urban datasets) to predict lateral and longitudinal maneuvers with uncertainty bounds.
- Propagates these bounds into the MILP optimizer as chance constraints—e.g., phase extension only if P(human stop) > 0.9P(\text{human stop}) > 0.9P(human stop) > 0.9.
- Emits graded advisories (“45–55 km/h recommended”) rather than a single speed, acknowledging variability and boosting adherence by up to 12 %.

Equity and Policy Alignment

Left unchecked, the system might allocate excessive green time to premium AV shuttles at the expense of buses or cyclists. To safeguard inclusivity, the CO embeds a multi-objective weighting vector that city councils can tune via policy dashboards:

- Efficiency weight (delay, emissions) vs. equity weight (person-throughput, sidewalk wait-time).
- Time-of-day profiles (e.g., +50 % transit priority during school egress).
- “Equity audits” log every optimization cycle; monthly reports flag corridors where vulnerable users see >10 % worse performance, triggering manual review or automatic weight re-balancing.

Scalability

MILP complexity scales roughly O(n1.8)O(n^{1.8})O(n1.8) with intersections nnn. For a 250-intersection city, a naïve global solve would exceed 1 s—too slow for 30-s horizons. The architecture therefore:

1. **Graph Partitioning:** Road network is cut into overlapping corridor clusters (≤ 25 nodes) using METIS, minimizing inter-cluster flow.
2. **Hierarchical Solve:** Each CC solves its sub-MILP in parallel on GPUs; the CO then reconciles boundary flows via Benders cuts—an iterative constraint-pruning technique that converges within three rounds.
3. **Any-time Guarantees:** If compute hits the 300 ms cap, the current best-feasible solution is dispatched; subsequent cycles warm-start from that point, ensuring no missed actuation windows.

SCOPE FOR IMPLEMENTATION AND SCALABILITY

Pilot-Scale Deployment

A plausible starting point is a university research corridor abutting a congested arterial. Deploying seven adaptive signals, three dedicated AV lanes, and two edge servers can validate control logic before city-wide scaling.

Incremental Rollout Strategy

1. **Digital Twin Development** – Build a high-fidelity simulation model of existing traffic patterns.
2. **Parallel Shadow Mode** – Run integrated control in the background, measuring improvements without live actuation.
3. **Progressive Activation** – Enable dynamic lane reassignment during off-peak hours; gradually extend to peak periods upon validation.

Regulatory Alignment

Close collaboration with road authorities ensures compliance with signal priority rules, pedestrian-crossing mandates, and data privacy regulations under local transport acts.

RESULTS FROM SIMULATED CASE STUDY

Testbed Configuration

A 14 km corridor in a mid-sized Indian city was modeled, comprising 12 signalized intersections and one expressway section reserved for autonomous shuttles. Peak-hour demand reached 4 300 Passenger Car Units (PCUs) per hour.

Performance Metrics

- Average Network Delay fell from 86 s to 54 s (–37 %).

- Travel Time Reliability (95th/50th percentile) improved from 2.1 to 1.4.
- Energy Consumption (fuel-equivalent, including electric AV battery draw) dropped 22 %.
- Conflict Points (proxy for safety) decreased 18 % owing to smoother platoon arrivals and reduced red-light running.

Discussion

Results underscore the importance of bidirectional data sharing. When corridor controllers throttled platoon releases based on upstream queue occupancy, spillback vanished and signal offsets stabilized—benefits that neither standalone adaptive signals nor isolated corridor control achieved.

Table: 1 Comparison of Conventional Vs. Integrated System Performance

Metric	Conventional STCS Only	Integrated AV–STCS System	Improvement (%)
Average Network Delay (sec)	86	54	–37%
Travel Time Reliability (P95/P50)	2.1	1.4	–33%
Fuel-equivalent Energy Use	100%	78%	–22%
Conflict Points per Hour	120	98	–18%

FUTURE WORK

- Real-World Field Trial across heterogeneous climates to test sensor robustness in monsoon conditions.
- Integrated Payment and Tolling so that dynamic road-use pricing nudges mode switching in real time.
- Machine Learning Explainability modules to translate optimization decisions into operator-friendly narratives, enhancing trust and facilitating regulatory approval.
- Pedestrian and Cyclist Safety Extensions integrating wearable V2P (vehicle-to-pedestrian) devices for vulnerable road users.

CONCLUSION

Integrating smart traffic control systems with autonomous vehicle corridors shifts the focus from local optimizations to holistic network orchestration. By unifying sensors, signals, RSUs, and corridor controllers under a fast, secure edge-to-cloud platform, cities can realize dramatic gains in delay reduction, energy savings, and safety—even while mixed fleets dominate the road. Our simulated 14 km deployment demonstrates the power of coordinated control, revealing that siloed deployments leave untapped synergies on the table. As autonomous penetration grows, the outlined framework offers a pragmatic path for metropolitan agencies to harness emerging technologies without sacrificing equity, resilience, or fiscal prudence.

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