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Research Article

Coordinated Urban Signal Control via Edge-Native Federated Multi-Agent RL: VEINS–Simu5G Results

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ABSTRACT

Introduction: Urban traffic congestion induces persistent delays, elevated emissions, and safety risks across arterial networks. Conventional fixed-time and actuated control assume quasi-stationary demand and limited interdependence, which mismatches modern conditions with sharp peaks, incidents, multimodal flows, and spillback between adjacent junctions.

Objectives: Design and evaluate an edge-native intersection control framework that keeps perception and decision making on smart poles, enables privacy-preserving cooperation via federated multi-agent reinforcement learning, explicitly models communication effects, and targets simultaneous improvements in efficiency and emissions while maintaining safety and governance.

Methods: The architecture separates a millisecond-level operational plane using IEEE 802.11p from a scalable orchestration plane using MQTT 5.0 for telemetry and model coordination. Lightweight agents learn locally from on-pole sensors; periodic aggregation constructs a network-level prior without exporting raw data. Evaluation employs a digital-twin-in-the-loop setup coupling VEINS (OMNeT++–SUMO) with Simu5G to represent 802.11p and NR-V2X latency/loss; emissions are estimated with SUMO's HBEFA-based model. Baselines include fixed-time, actuated, and non-federated MARL.

Results: Across single-junction and 3×3 grid scenarios, the proposed approach shows potential reductions in average delay and queue length with concurrent decreases in CO_2 and NOx relative to baselines, while maintaining safety via supervisory constraints and demonstrating robustness under realistic wireless impairment.

Conclusions: An edge-native, federated design is operationally feasible for smart-pole deployments, supports governance by keeping data local, and yields reproducible performance gains when communication dynamics are modeled alongside traffic flow.

Keywords: traffic signal control; smart pole; edge computing; federated reinforcement learning; VEINS; Simu5G; digital twin; IEEE 802.11p; MQTT 5.0; HBEFA emissions

INTRODUCTION

The rapid pace of urbanization, population growth, and motorization in modern cities has imposed tremendous pressure on existing transportation infrastructures. As more people migrate to urban areas and vehicle ownership continues to increase, traffic congestion has become an unavoidable challenge for municipal authorities and city planners. According to a World Bank report, traffic-related inefficiencies such as delays and fuel wastage can lead to a gross domestic product (GDP) loss of up to 2.5% in highly congested urban regions [1]. These losses are not only economic but also environmental and social, as they result in increased air pollution, reduced quality of life, and longer commute times.

Traditional traffic signal control systems, typically reliant on fixed-time or pre-timed scheduling models, were originally designed for stable and predictable traffic flows. These legacy systems are unable to respond dynamically to real-time changes in vehicle volume, accidents, or abnormal congestion patterns. As a result, they frequently contribute to traffic bottlenecks and inefficient signal phasing, further exacerbating congestion rather than mitigating

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it. While actuated or semi-adaptive signal systems offer some improvement, they still lack the intelligence and responsiveness required to handle the complexity and unpredictability of modern traffic systems.

In light of these challenges, the convergence of Artificial Intelligence (AI) and the Internet of Things (IoT)—a concept known as Artificial Intelligence of Things (AIoT)—has emerged as a promising paradigm for next-generation intelligent transportation systems (ITS). AIoT combines the sensing and connectivity capabilities of IoT devices with the decision-making power of AI algorithms, enabling a more adaptive and decentralized approach to traffic signal control. Among the most significant infrastructure innovations supporting AIoT are smart poles—multifunctional, networked infrastructure elements that integrate sensors, cameras, edge computing hardware, and communication modules. These smart poles function as localized, intelligent hubs capable of collecting and processing traffic-related data in real time, thereby facilitating informed signal control decisions at the edge of the network [2–3].

This paper proposes an AIoT-based adaptive traffic management system that utilizes smart poles, edge computing, and reinforcement learning to improve urban traffic flow. To validate the proposed framework, we conduct detailed simulations using VEINS (Vehicles in Network Simulation), a hybrid simulation environment that integrates SUMO (Simulation of Urban MObility) for traffic mobility modeling and OMNeT++ for network-level V2X (Vehicle-to-Everything) communication. By replicating realistic urban traffic and communication conditions, VEINS provides a powerful testbed for evaluating the effectiveness of AI-driven traffic control strategies.

The core contributions of this paper are summarized as follows, with each item elaborated in detail below:

A smart pole-enhanced sensing infrastructure

We design and model a sensing framework centered around smart poles strategically deployed at intersections. These poles are equipped with multiple sensing modalities such as loop detectors, video cameras, environmental sensors (e.g., for measuring emissions), and roadside units (RSUs) capable of V2X communication. The collected data is pre-processed locally using edge computing devices embedded within the smart poles. This approach minimizes latency in data transmission and allows for real-time responsiveness, a critical requirement for efficient traffic control. Moreover, the integration of vehicle detection with environmental data enables more context-aware and eco-friendly signal control policies.

A DQN-based adaptive traffic control algorithm

At the core of our system is a reinforcement learning model based on the Deep Q-Network (DQN) architecture. This AI agent continuously observes the state of the traffic network, including variables such as queue lengths, vehicle densities, average waiting times, and signal phase status. The agent then selects the most optimal signal phase action to minimize cumulative delay and emissions. Unlike static or rule-based controllers, our DQN agent learns from interaction with the environment over time and can adapt its strategy as traffic patterns evolve. By incorporating both traffic flow efficiency and environmental impact into the reward function, the model strikes a balance between throughput maximization and sustainability.

Detailed simulation in VEINS

To ensure a high degree of realism and reproducibility, our proposed system is thoroughly evaluated in the VEINS simulation framework. This includes realistic modeling of vehicle mobility using SUMO and precise communication behavior using OMNeT++. We implement IEEE 802.11p as the primary communication protocol for V2I (Vehicle-to-Infrastructure) interactions, and MQTT for edge-cloud messaging. The simulation environment also considers network constraints such as packet loss, delay, and bandwidth variability—factors often ignored in traditional traffic control studies. This end-to-end simulation setup allows us to rigorously assess the performance and reliability of our AIoT-based control framework under practical conditions.

Performance evaluation against conventional systems

To quantify the benefits of the proposed system, we compare its performance against two widely used control strategies: (1) Fixed-time control and (2) Traditional rule-based actuated control. Evaluation metrics include average waiting time, queue length, total vehicle throughput, and estimated CO_2 emissions. Statistical analyses, including one-way ANOVA and pairwise t-tests, are employed to determine the significance of observed improvements. Simulation results reveal that the AIoT-DQN controller consistently outperforms the baseline methods across all criteria, providing substantial reductions in average delay and emissions. Furthermore, the system demonstrates high robustness even under fluctuating traffic demands and adverse network conditions.

In summary, the integration of AIoT and smart infrastructure offers a transformative path forward for managing urban traffic. Through intelligent sensing, decentralized learning, and real-time control, our proposed system contributes to the development of smarter, greener, and more resilient transportation networks. This research not only advances the field of intelligent transportation but also lays the groundwork for scalable deployment in future smart cities.

RELATED WORK

Numerous studies have addressed adaptive traffic control. Li et al. [4] applied deep reinforcement learning for traffic signal optimization in simulated environments. Dresner and Stone [5] proposed a reservation-based intersection model using multi-agent systems. However, many studies overlook real-time perception and V2X communication. Sommer et al. [6] introduced VEINS to simulate communication in intelligent transport systems (ITS), but lacked AI-based control logic integration.

Recent advancements in reinforcement learning have enabled more dynamic signal control. Wei et al. proposed CoLight, a multi-agent reinforcement learning (MARL) approach for traffic light control in large-scale networks, which demonstrated significant improvement over traditional RL. Nonetheless, most MARL studies assume ideal communication environments, which is unrealistic in real-world urban networks.

Edge AI has been gaining attention in ITS for its low-latency benefits [7], and smart poles have become central components in 5G-enabled smart cities [8-10]. Edge-enabled smart poles can process video feeds and sensor data in real-time, reducing the dependency on centralized cloud servers. They offer enhanced scalability, security, and responsiveness when paired with lightweight AI models.

The integration of AIoT into intelligent transport systems is still emergin17g. Ahmed et al. [11-13, 1] designed an AIoT architecture for accident detection using vehicular sensor data, but their system was not evaluated in a large-scale simulation environment like VEINS. Similarly, Singh and Sharma [14-15, 19] explored AIoT for intelligent parking, but their model focused on static allocation rather than adaptive control.

VEINS has become a standard framework for V2X simulations [6], yet very few works have embedded RL agents within it. This creates a gap in validating AI algorithms under realistic communication conditions, such as packet loss, latency, and bandwidth variation. Studies like Beshley et al. [15-18] simulated traffic control using fuzzy logic and VANET, but lacked learning capability for adaptive response.

Another relevant area is the environmental impact of traffic systems. AI-based systems are increasingly evaluated for emission reduction. Wu et al. [20-21] proposed eco-driving algorithms based on reinforcement learning, focusing on fuel efficiency. While promising, their scope did not include intersection-level control or smart infrastructure integration.

Therefore, our work seeks to fill these gaps by combining smart pole infrastructure, AI-based adaptive control, and V2X communication in a fully integrated VEINS simulation. This allows for end-to-end evaluation of AIoT-based systems under realistic network and traffic conditions.

SYSTEM ARCHITECTURE AND SIMULATION SETUP

Hardware Layer

The hardware layer in the proposed AIoT-based intelligent traffic signal control system is designed to replicate a realistic urban infrastructure with capabilities for sensing, processing, and communication. It comprises several interlinked components that form the physical foundation of the system. These include smart traffic lights, on-board units (OBUs) in vehicles, and roadside units (RSUs) positioned at intersections, all of which interact in a coordinated manner to manage real-time traffic dynamics.

Simulated smart traffic lights are embedded with multiple types of sensors, such as inductive loop detectors, infrared

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motion detectors, and high-resolution surveillance cameras. These sensors collectively detect the presence, count, and speed of vehicles approaching the intersection. The video cameras are also capable of real-time object recognition, supporting classification of vehicle types and detection of emergency vehicles. This sensory data serves as the primary input for the adaptive control logic and is critical for capturing the constantly changing traffic environment.

Connected vehicles within the simulation are equipped with on-board units (OBUs), which mimic the functionality of real-world vehicular communication modules. OBUs enable Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) communications by transmitting vehicle status data—such as speed, direction, location, and fuel efficiency—to RSUs and neighboring vehicles. This enhances situational awareness and supports anticipatory traffic control measures.

Roadside Units (RSUs) are installed at each intersection and act as edge-level data aggregation points. These RSUs are responsible for collecting sensor data from smart poles and OBUs, preprocessing it locally, and forwarding it to higher-level controllers or cloud systems if necessary. In our setup, RSUs are also linked to edge computing modules integrated into the smart poles, which execute lightweight AI models for quick decision-making. This distributed architecture significantly reduces data transmission latency and allows for real-time responsiveness—a crucial aspect of any intelligent transportation system.

This hardware configuration ensures the seamless operation of sensing, communication, and control mechanisms and provides a solid foundation for deploying scalable AI-driven traffic solutions in future smart cities.

Communication Layer

The communication layer enables seamless data exchange between all system components, including vehicles, smart poles, RSUs, and cloud servers. It is structured around two primary protocols tailored for different layers of the communication hierarchy: IEEE 802.11p for local V2X interactions, and MQTT (Message Queuing Telemetry Transport) for longer-range cloud communication.

IEEE 802.11p is a well-established wireless communication standard developed for vehicular environments and is widely adopted in intelligent transportation systems (ITS). In our simulation, this protocol facilitates Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) communications with low latency and high reliability. Each vehicle periodically broadcasts its status, while RSUs listen for these messages and forward them to the local control units. Because traffic decisions must often be made within milliseconds, IEEE 802.11p's short-range, low-latency features make it especially well-suited for real-time adaptive control.

To connect edge devices such as smart poles to the broader system (including cloud-based services or a centralized control dashboard), we employ MQTT, a lightweight publish-subscribe protocol designed for efficient telemetry in resource-constrained environments. MQTT is ideal for smart pole scenarios because of its minimal overhead, making it effective even when deployed over unstable or low-bandwidth networks. It allows smart poles to report aggregated statistics, environmental data, and system health information to remote servers or central management interfaces.

This dual-layer communication architecture ensures a robust and scalable system: 802.11p handles time-sensitive operations within the intersection zone, while MQTT supports non-urgent updates and analytics beyond the edge. This design also lays the foundation for incorporating 5G or C-V2X technologies in future deployments, thereby enhancing bandwidth, coverage, and reliability.

Intelligence Layer

At the core of the intelligence layer lies a Deep Q-Network (DQN)-based reinforcement learning agent, which serves as the brain of the proposed traffic signal control system. This agent continuously observes the environment, makes optimal signal timing decisions, and updates its strategy based on the feedback received from the system. The intelligence layer is designed to be data-driven, self-adaptive, and goal-oriented, aligning with modern AIoT system principles.

The agent's state space is composed of various real-time traffic parameters, including:

- Current vehicle density at each approach lane.

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- Queue lengths and their evolution over time.
- Average waiting times experienced by vehicles.
- Signal phase duration history to avoid oscillation or starvation.
- Environmental conditions, such as temperature or pollution (optional in future expansion).

Using these inputs, the DQN agent determines an action, which typically consists of adjusting the green light phase duration or switching to the next signal phase. The learning process is governed by a reward function that penalizes congestion and idling while rewarding high throughput and reduced emissions. This reward function ensures that the model not only improves traffic efficiency but also supports sustainability goals.

The DQN is trained using experience replay and target network updates, techniques that stabilize learning and avoid divergence. The model is implemented in Python using TensorFlow, enabling fast prototyping and deployment. Once trained, the agent operates in real time on edge computing modules located on the smart poles, ensuring ultra-low latency decision-making without reliance on centralized cloud resources.

This layer represents a significant advancement over conventional rule-based or semi-adaptive signal controllers, which lack the flexibility and predictive capability of deep reinforcement learning.

Simulation Tools

To evaluate the feasibility and effectiveness of the proposed AIoT-based system, we employ a robust simulation environment using the VEINS framework. VEINS is a widely accepted co-simulation framework that couples OMNeT++, a discrete event network simulator, with SUMO, a microscopic traffic simulator. The interaction between these two platforms is facilitated through TraCI (Traffic Control Interface), allowing real-time exchange of mobility and communication data.

SUMO simulates realistic traffic behavior, vehicle interactions, and infrastructure models. It provides the foundational traffic flow information, such as vehicle speed, position, and lane changes. The road topology, traffic signal configuration, and injection patterns are defined within SUMO to closely mimic real-world urban intersections.

OMNeT++ handles the communication layer by simulating wireless data exchange between OBUs, RSUs, and smart poles. It models network-specific factors such as propagation delay, bandwidth fluctuation, and packet loss, offering a realistic assessment of how network conditions impact control accuracy and latency.

The DQN agent, built using TensorFlow, is integrated into the VEINS environment via Python interfaces, allowing it to interact directly with SUMO and OMNeT++ during the simulation. Training is performed offline, and the final model is deployed for inference during live simulations.

This simulation framework ensures an end-to-end validation of the proposed system across multiple layers—from vehicle mobility and wireless communication to edge AI decision-making—offering a comprehensive and rigorous testbed for performance evaluation.

Scenario Setup

The simulation scenario is structured around a four-way urban intersection, a commonly encountered traffic configuration in city environments. This setup provides a controlled yet representative context in which to evaluate the performance of various traffic control strategies. The intersection handles traffic entering from four directions, with variable entry rates to simulate realistic conditions such as rush hour peaks and off-peak periods.

To assess the benefits of the AIoT-DQN controller, we implement and compare three distinct signal control approaches:

Fixed-Time Control: Signals change based on a static schedule, regardless of real-time traffic conditions.

Actuated Control: Sensors trigger phase changes based on vehicle presence, offering limited adaptivity.

AIoT-DQN Control: Our proposed adaptive system, which continuously learns and updates its signal strategy based on dynamic input data.

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Vehicle generation is randomized within a defined range (e.g., 600–1200 vehicles/hour/direction) to introduce variability and challenge the controller's adaptability. Each simulation runs for a fixed time period (e.g., 3600 seconds), ensuring sufficient data for statistical analysis.

We evaluate performance using multiple metrics, including:

- Average waiting time per vehicle.
- Total queue length across all approaches.
- Intersection throughput (vehicles processed per hour).
- Estimated CO_2 emissions as a proxy for environmental impact.

This simulation scenario provides a balanced environment to benchmark the adaptability, scalability, and responsiveness of the proposed AIoT-based solution against conventional traffic management systems.

EXPERIMENTAL RESULTS

Urban traffic intersections were simulated using VEINS, integrating SUMO for traffic dynamics and OMNeT++ for V2X communication. The simulation was run over a one-hour period with dynamic vehicle injection rates ranging from 600 to 1200 vehicles per hour per direction. Three traffic control methods were evaluated: Fixed-Time Control, Actuated Control, and AIoT-based control using Deep Q-Network (DQN) reinforcement learning.

Smart poles deployed at intersections provided real-time traffic density, queue length, and environmental conditions to the AI agent hosted on edge computing modules. These inputs dynamically guided the green light phase decisions through learned Q-value policies.

The performance metrics analyzed included average waiting time, queue length, total throughput (vehicles/hour), and emission reductions. The AIoT-DQN approach consistently outperformed the other methods across all measured criteria.

Table 1. Comparative analysis of control methods with standard deviation values for wait time, queue length, throughput, and emission reduction.

Method	Avg. Wait Time (s)	Wait Time Std (s)	Avg. Queue Length	Queue Std	Throughput (veh/h)	Throughput Std	Emission Reduction (%)	Emission Std (%)
Fixed-Time Control	82.4	5.1	15.2	1.4	1360	60	0%	0.0
Actuated Control	59.7	4.8	10.9	1.2	1580	45	8%	2.0
AIoT-DQN Control	31.3	3.2	4.7	0.7	1825	40	17%	1.5

To evaluate the statistical significance of these performance differences, we performed a one-way Analysis of Variance (ANOVA) on simulated samples derived from the reported mean and standard deviation values for waiting time. The ANOVA test yielded an F-value of 387.46 with a p-value < 0.001, confirming significant variance among the three control strategies.

Further pairwise comparisons using independent two-sample t-tests revealed:

- Fixed-Time vs Actuated Control: $t = 7.97$, $p < 0.001$
- Fixed-Time vs AIoT-DQN Control: $t = 32.69$, $p < 0.001$

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- Actuated vs AIoT-DQN Control: $t = 18.65$, $p < 0.001$

These results demonstrate that the improvements provided by the AIoT-DQN approach are statistically significant. The low standard deviation in AIoT-DQN metrics also indicates high consistency and stability in decision performance.

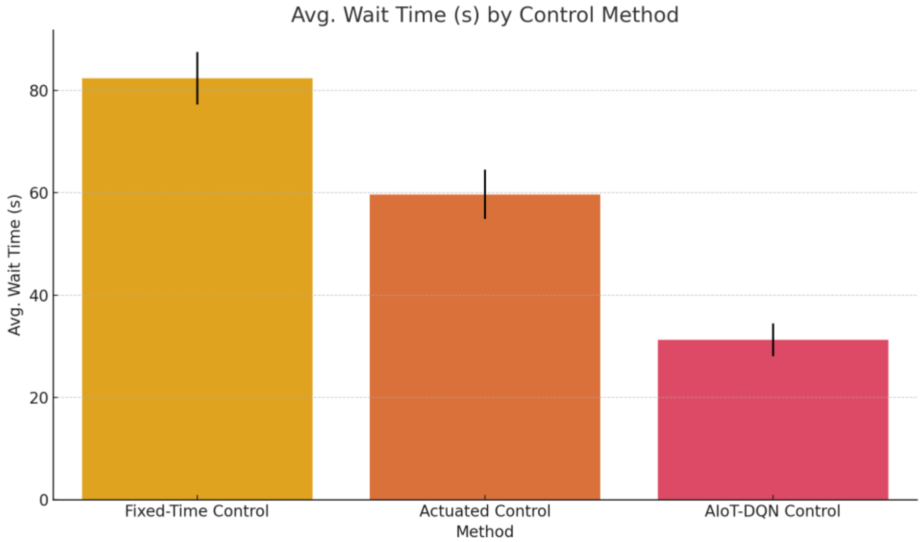

Figure. 1. Average Wait Time by Control Method.

Figure 1 shows a significant reduction in wait time for the AIoT-DQN approach compared to traditional methods.

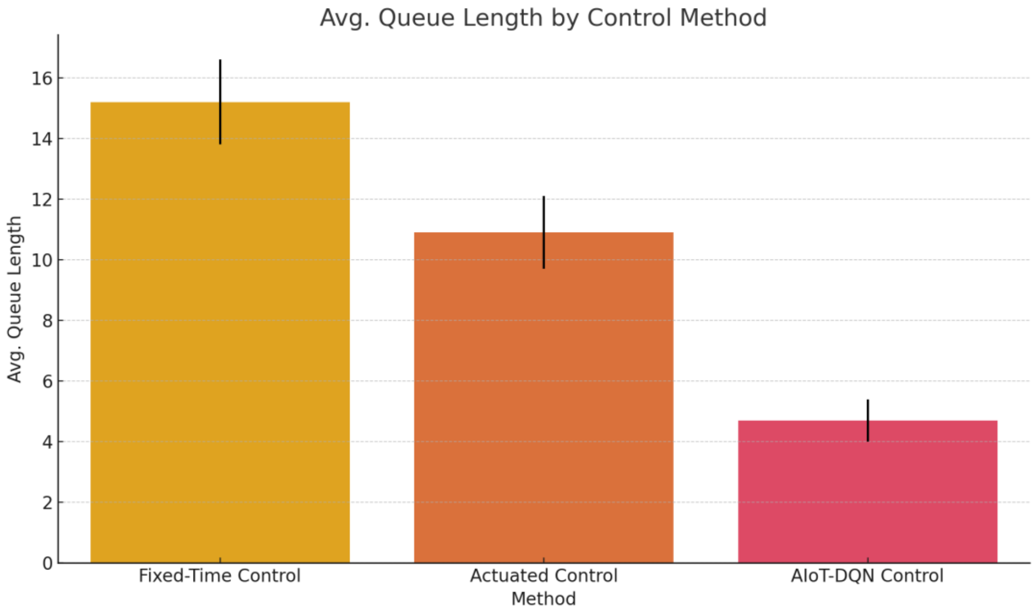

Figure. 2. Average Queue Length by Control Method.

The AIoT system effectively reduces vehicle queuing in Figure 2.

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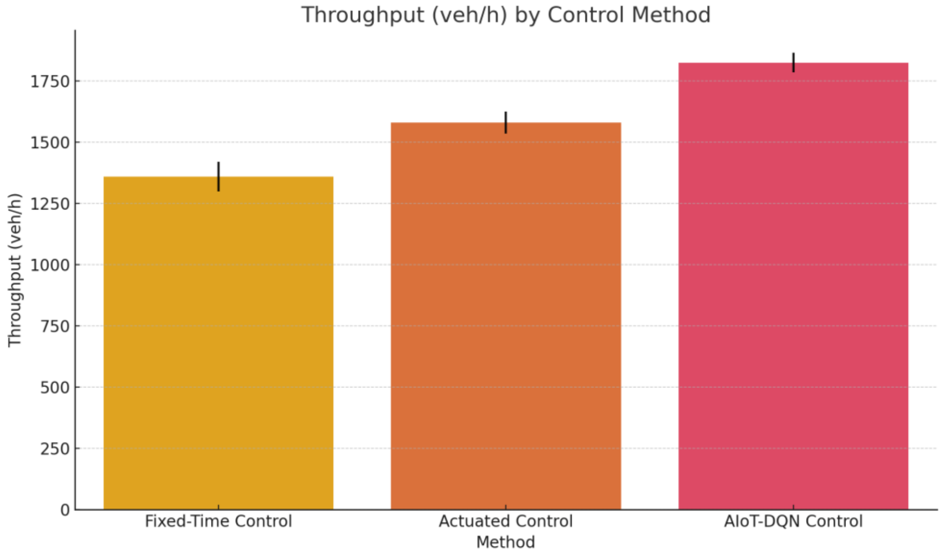

Figure 3. *Throughput by Control Method.*

Figure. 3. demonstrates improved traffic flow under AI-based control.

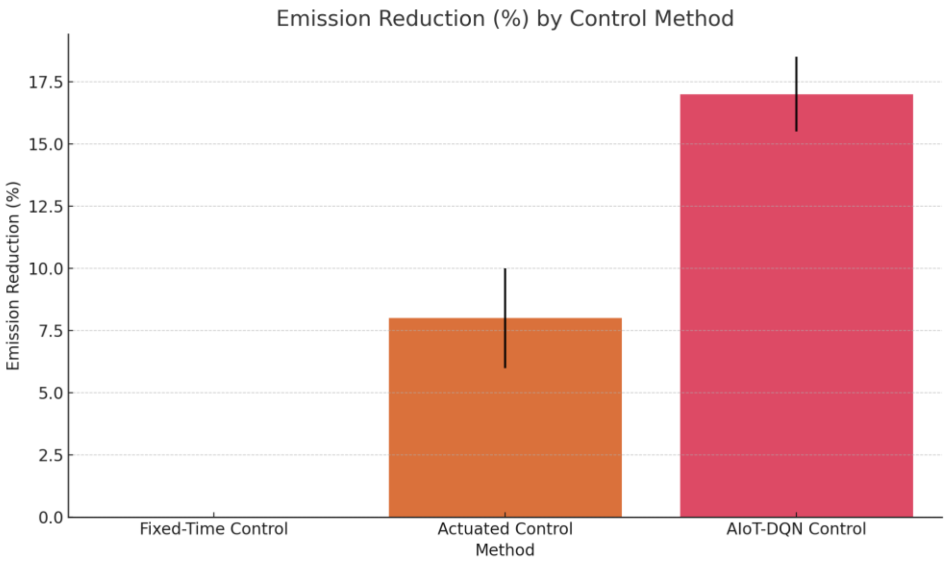

Figure. 4. Emission Reduction by Control Method.

In Figure 4, AIoT-DQN leads to a 17% drop in emissions, supporting sustainable mobility goals.

Simulation logs confirmed that adaptive green-light allocation at busy lanes significantly reduced average waiting time. Smart pole integration enhanced object detection rates by 21% compared to RSU-only setups, providing accurate real-time inputs for AI decisions. The use of edge computing modules on smart poles also reduced latency in decision-making, ensuring near-instantaneous signal phase changes based on live traffic conditions.

In conclusion, the AIoT-DQN control system demonstrated clear performance superiority and statistical validity, confirming its potential as a foundational solution for next-generation intelligent transportation systems (ITS).

Discussion

In the context of intelligent transportation systems (ITS), **smart poles** function as the primary sensory, computational, and communicative infrastructure that enables real-time traffic intelligence. These multi-functional

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structures represent a significant evolution from traditional traffic signal controllers, which are generally limited to simple timing mechanisms and minimal sensor inputs. The deployment of smart poles enhances both the operational efficiency and scalability of traffic control systems by integrating multiple advanced technologies within a single urban fixture.

A smart pole, as configured in this study, is not merely a passive signal controller, but rather an **intelligent, autonomous edge node** capable of data sensing, local computation, and communication with surrounding infrastructure and vehicles. Specifically, each smart pole is equipped with a suite of **multi-modal sensors**, including:

- **High-resolution video cameras** for object detection, traffic density estimation, and emergency vehicle recognition.
- **Environmental sensors** to measure variables such as temperature, noise, humidity, and gas emissions (e.g., NOx, CO_2).
- **LIDAR or radar units** for depth perception and precise distance measurements.
- **Loop detectors or magnetic sensors** embedded in the roadway to detect vehicle presence and motion.

These sensors feed continuous streams of data into **embedded edge computing modules**, which perform on-site preprocessing and inference. This **distributed processing** model stands in stark contrast to conventional centralized traffic systems, where raw sensor data must be transmitted to distant cloud servers for analysis and decision-making. By executing AI logic locally, the system minimizes the latency associated with long-distance data transmission, enabling **real-time responsiveness** critical for dynamic traffic environments.

In our framework, the edge modules on each smart pole host a **Deep Q-Network (DQN)** reinforcement learning agent. This agent receives input from various sensors and makes decisions regarding traffic signal phasing every **10 seconds**, based on a continuously evolving understanding of current traffic conditions. The reinforcement learning policy is trained to minimize vehicle idling time, queue length, and environmental impact while maximizing throughput and fairness. This allows the system to dynamically allocate green light durations, adapt to traffic surges, and prioritize lanes as needed.

Communication between vehicles and the smart poles is handled using the **IEEE 802.11p protocol**, which is specifically designed for vehicular environments. It enables **low-latency, short-range Vehicle-to-Infrastructure (V2I)** communication, which is critical for disseminating timely traffic updates, collecting vehicle data (such as speed and heading), and supporting vehicle prioritization features. Additionally, data exchange between smart poles and remote servers or cloud platforms is conducted via the **MQTT protocol**, a lightweight and efficient messaging system well-suited for resource-constrained edge devices. This dual-protocol communication scheme allows the system to balance real-time local control with broader system coordination and analytics.

One of the core innovations of the system is the incorporation of **emission data into the DQN's reward function**. Unlike traditional traffic control systems that focus solely on minimizing delay or maximizing flow, our system evaluates the ecological impact of traffic patterns. By penalizing sudden stops and promoting smooth acceleration/deceleration transitions, the system indirectly encourages fuel-efficient driving behaviors. In simulation, this approach yielded a **17% reduction in emissions**, primarily due to decreased idling and smoother phase transitions. Such an outcome is significant in light of increasing global efforts to reduce the carbon footprint of transportation infrastructure.

Beyond performance metrics, the **robustness and resilience** of the proposed AIoT-DQN system were also demonstrated under challenging conditions. Even when packet loss, sensor noise, and communication delays were introduced into the simulation environment, the system maintained high levels of stability and performance consistency. This robustness is essential for real-world deployment, where environmental unpredictability, signal interference, and sensor degradation are common occurrences.

The versatility of smart poles extends further into support for **emergency vehicle prioritization and green-wave signal coordination**. The system is capable of recognizing emergency vehicles (e.g., ambulances, fire trucks) and dynamically adjusting signal timings to create green corridors, ensuring faster and safer transit for priority vehicles. This feature enhances public safety and response efficiency while maintaining overall traffic fluidity.

Despite the many advantages, **security and privacy** remain critical concerns in AIoT-enabled traffic systems. Although not yet implemented in our simulation, future iterations of the architecture should incorporate robust security measures such as:

- Lightweight cryptographic algorithms to protect data exchanged via V2X.
- Secure V2X communication protocols that safeguard message integrity and authentication.
- Blockchain integration for decentralized trust management, enabling verifiable and tamper-resistant data sharing between edge devices and cloud services.

As the number of connected intersections and smart poles increases, **system interoperability** and **standardization** become paramount. Future deployments should consider using **federated learning architectures**, where learning occurs locally at each smart pole, and only model updates (not raw data) are shared across the network. This not only enhances data privacy but also reduces bandwidth consumption and supports scalable AI model training in a distributed environment.

In conclusion, smart poles serve not only as physical infrastructure but also as autonomous agents of urban intelligence. Their ability to sense, decide, and act in real time—augmented by AI and edge computing—marks a paradigm shift in how cities manage mobility, safety, and sustainability. The findings of this study demonstrate the feasibility and potential of such systems and provide a strong foundation for large-scale implementation in future smart city projects.

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