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"Reinforcement Learning for Intelligent Traffic Signal Control with Vehicle-Mounted IoT Sensors"

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Abstract- Adaptive traffic signal control is an important requirement for reducing urban congestion and improving traffic flow in smart cities. Traditional fixed-time signal systems work on pre-defined schedules and cannot respond effectively to sudden changes in traffic demand, peak-hour congestion, road incidents, or uneven lane usage. This research paper presents an intelligent traffic signal control system that combines Reinforcement Learning (RL) with vehicle-mounted Internet of Things (IoT) sensors. In the proposed system, vehicles provide anonymized and aggregated traffic information such as position, speed, lane approach, queue formation, and movement direction. This information is collected by roadside aggregation units and used by reinforcement learning agents to dynamically select signal phases at intersections. The main objective of the system is to reduce average waiting time, queue length, unnecessary stops, vehicle idling, and unfair lane delays while maintaining data privacy. A multi-agent Advantage Actor-Critic based approach is considered for controlling multiple intersections, and other RL algorithms such as Q-learning, Deep Q-Network, and Proximal Policy Optimization may also be applied depending on the traffic environment. The system is evaluated through SUMO-based traffic simulation. The study shows that RL-based signal control can improve performance compared with fixed-time and threshold-based control methods, with preliminary simulation results indicating approximately 30% improvement in waiting time and queue length. The paper also discusses methodology, deployment process, scalability, communication challenges, privacy protection, limitations, and future scope of RL-IoT based intelligent traffic management.

Keywords: Reinforcement Learning, Intelligent Traffic Signal Control, Vehicle-Mounted IoT Sensors, SUMO Simulation, Multi-Agent System, Smart City, Adaptive Traffic Management, Queue Reduction, Waiting Time Optimization, Traffic Congestion.

I. INTRODUCTION

Urban traffic congestion is one of the most serious problems faced by modern cities. Rapid urbanization, population growth, and the increasing number of vehicles have created long delays, fuel wastage, higher accident risk, air pollution, and reduced productivity. Road capacity and signal infrastructure often remain limited, so efficient traffic signal control becomes essential for smooth urban mobility.

Fixed-time traffic signals are simple to install and manage, but they are not suitable for highly dynamic traffic conditions. During peak hours, one approach may have a long queue while another approach may remain almost empty. A fixed signal plan cannot identify this condition in real time and may continue to provide green time based on a pre-set schedule. This causes unnecessary delays and increases congestion.

Some adaptive traffic management systems already use roadside sensors, loop detectors, and surveillance cameras. However, these systems can be costly to install, difficult to maintain, and limited in scalability. Vehicle-mounted IoT sensing provides an alternative because useful traffic information can be collected from moving vehicles themselves instead of depending only on fixed infrastructure.

Reinforcement Learning is a branch of machine learning in which an agent learns the best action by interacting with the environment. In traffic signal control, the RL agent observes the traffic condition, selects a signal phase, receives feedback in the form of reward, and improves its decision-making policy over time. This makes RL useful for adaptive signal control because it can learn from changing traffic patterns instead of depending only on manual timing plans.

Vehicle-mounted IoT sensors provide an additional advantage by offering real-time traffic information directly from vehicles. Sensors such as GPS devices, on-board units, and smartphones can provide speed, location, lane approach, and movement direction. When this data is aggregated and anonymized, it can help traffic controllers understand the actual traffic condition without violating driver privacy.

II. NEED FOR THE STUDY

The need for this study arises from the limitations of traditional traffic signal control systems. Many intersections still use fixed signal timings that are prepared using historical traffic data. Such systems cannot respond properly to sudden congestion, road accidents, special events, weather conditions, or changes in traffic volume throughout the day.

Traffic congestion directly affects citizens by increasing travel time and fuel consumption. It also increases vehicle emissions and creates environmental problems. From the city management point of view, inefficient signal control reduces road capacity and creates pressure on transport infrastructure. Therefore, intelligent and adaptive signal control is required for smart city development.

Recent developments in IoT and connected vehicle technology make it possible to collect useful traffic data from vehicles themselves. At the same time, reinforcement learning provides a strong decision-making mechanism for selecting signal timings based on real-time traffic states. This study is important because it combines these two technologies to propose a practical and scalable intelligent traffic signal control system.

This study is also required because smart city traffic systems must be scalable and privacy-preserving. By using only aggregated values such as vehicle count, average speed, and estimated queue length, the proposed approach can support intelligent decision-making without storing personal vehicle identity or driver information.

III. OBJECTIVES OF THE STUDY

1. To study the role of reinforcement learning in intelligent traffic signal control.
2. To understand how vehicle-mounted IoT sensors can provide useful real-time traffic data.
3. To design a privacy-preserving traffic data aggregation method for intersections.
4. To formulate signal phase selection as a reinforcement learning problem.
5. To compare the proposed RL-IoT system with fixed-time and actuated signal control methods.
6. To reduce average waiting time, queue length, number of stops, and vehicle idling.
7. To identify limitations, deployment challenges, and future opportunities for smart traffic management.
8. To improve fairness across lanes by dynamically balancing green light duration according to real-time demand.

IV. PROBLEM STATEMENT

Traffic signal control is a complex problem because traffic demand changes continuously. Traditional signal systems use fixed timings or simple detector-based rules, which are not always capable of handling dynamic traffic flow. When the actual traffic condition is different from the planned timing schedule, vehicles may wait unnecessarily at red signals, queues may increase, and congestion may spread to nearby intersections.

Another challenge is the lack of accurate and real-time traffic state information. Infrastructure sensors such as cameras and loop detectors can be expensive to install and maintain. In some locations, these sensors may not provide complete coverage. Vehicle-mounted IoT sensors can help solve this issue by providing traffic information from the vehicles themselves. However, this data must be used carefully to protect privacy and security.

In addition to sensing limitations, large-scale deployment must also handle network latency, data reliability, secure communication, and standardization of vehicle-to-infrastructure communication protocols. These challenges must be considered before using RL-IoT traffic control in real city environments.

Therefore, the problem addressed in this paper is how to develop an intelligent traffic signal control system that uses aggregated vehicle-mounted IoT data and reinforcement learning to optimize signal phases in real time while reducing congestion and maintaining privacy.

V. LITERATURE REVIEW

Many researchers have studied reinforcement learning for adaptive traffic signal control. Early studies used Q-learning methods for individual intersections. These systems showed that a traffic controller could learn signal decisions based on traffic feedback, but they were limited when the number of lanes, phases, and intersections increased.

Recent reviews have highlighted Q-learning, Deep Q-Network, Actor-Critic, and federated reinforcement learning as important methods for traffic signal control. Studies on federated DQN and distributed RL show that traffic agents can learn from local conditions while reducing the need to share sensitive raw data. These methods are useful for privacy-preserving smart city applications.

Deep reinforcement learning techniques improved this field by using neural networks to handle large state spaces. Methods such as Deep Q-Networks, Actor-Critic models, and Policy Gradient methods have been used for traffic signal optimization. Studies such as PressLight and CoLight show that RL-based systems can reduce delay and improve coordination among neighboring intersections.

Multi-agent reinforcement learning is especially important for city traffic networks because intersections are connected to each other. The decision made at one intersection can affect queues and vehicle flow at the next intersection. Multi-agent approaches allow each intersection to act as an independent agent while sharing limited information with nearby intersections.

IoT-based traffic management has also become an active research area. Cameras, roadside sensors, connected vehicles, and mobile devices can provide useful traffic data. Some studies have used surveillance-camera data and connected vehicle data for RL-based signal control. However, the use of vehicle-mounted IoT sensors with privacy-preserving aggregation across multiple intersections is still an emerging area.

Vehicle-mounted sensor research shows that speed, location, density, and lane usage data can help traffic monitoring systems estimate congestion more accurately. However, very few studies combine vehicle-mounted IoT sensing with RL-based signal phase decision-making. This gap makes the proposed approach distinctive because it connects real-time vehicle data collection with intelligent adaptive traffic control.

Simulation platforms such as SUMO are widely used for testing traffic signal control algorithms because direct testing on real intersections can be risky and costly. SUMO allows researchers to model road networks, traffic demand, vehicle movement, and signal behavior in detail. Therefore, simulation-based validation is suitable for the proposed research before field deployment.

VI. TECHNOLOGIES USED IN INTELLIGENT TRAFFIC SIGNAL CONTROL

Reinforcement Learning

Reinforcement Learning is used to train traffic signal agents. The agent observes the traffic state, chooses an action such as switching or extending a green phase, and receives a reward based on waiting time and queue reduction. Over repeated simulations, the agent learns which signal decisions produce better traffic flow.

Deep Reinforcement Learning Algorithms

Different RL algorithms can be used for this system. Q-learning can be applied to small traffic environments, while Deep Q-Network can handle larger state spaces using neural networks. Proximal Policy Optimization and Advantage Actor-Critic methods are useful for more complex and stochastic traffic conditions. The final selection of algorithm depends on the number of intersections, available data, and required stability of learning.

Multi-Agent System

In a city network, each intersection can be considered as one agent. A multi-agent system allows every intersection to make local decisions while also considering nearby traffic conditions. This helps reduce congestion not only at one junction but across the complete road network.

Vehicle-Mounted IoT Sensors

Vehicle-mounted IoT sensors include GPS units, smartphones, and connected vehicle devices. These sensors provide data such as vehicle speed, position, direction, and approach lane. The system uses only aggregated data so that individual drivers are not identified.

Data Aggregation Unit

The data aggregation unit receives vehicle observations and converts them into lane-level traffic features. These features may include number of vehicles, average speed, queue length estimate, and waiting time estimate. This layer also supports privacy by avoiding storage of personal vehicle information.

SUMO Simulation

SUMO is an open-source microscopic traffic simulator used to test traffic control algorithms. It can simulate vehicle movement, traffic signals, road networks, and congestion scenarios. In this research, SUMO is used to evaluate the RL-IoT traffic signal control approach before real-world deployment.

VII. APPLICATIONS OF RL-IOT TRAFFIC CONTROL

Urban Traffic Congestion Reduction

The proposed system can be used in busy urban intersections to reduce long queues and waiting time. By changing signal phases dynamically, the system can provide green time according to real-time traffic demand.

Smart City Traffic Management

Smart cities require data-driven transport systems. RL-IoT based signal control can become a part of smart city infrastructure by using real-time vehicle data, intelligent controllers, and connected traffic systems.

Emergency Vehicle Priority

The system can be extended to detect emergency vehicles such as ambulances and fire engines. The signal controller can then provide priority green signals to reduce emergency response time.

Fuel and Emission Reduction

When vehicles spend less time waiting at red signals, fuel consumption and emissions are reduced. This helps improve environmental quality and supports sustainable transportation goals.

Incident and Peak-Hour Management

During accidents, roadwork, or peak-hour traffic, the RL agent can adapt signal phases according to changing traffic conditions. This makes the system more flexible than fixed timing plans.

VIII. RESEARCH METHODOLOGY

This research follows a simulation-based and analytical methodology. The study first identifies the limitations of fixed-time traffic signal control and then proposes an RL-IoT based architecture. The traffic environment is modeled using SUMO, and vehicle-mounted IoT data is represented through simulated vehicle movement data such as position, speed, lane usage, density, and lane occupancy.

The reinforcement learning framework is defined using three main components. The state represents traffic conditions at an intersection, including vehicle density, average speed, estimated queue length, and waiting time. The action represents possible traffic light decisions such as changing phase duration, extending green time, or selecting the next phase. The reward is designed to reduce waiting time, minimize queue length, and balance traffic flow across lanes.

Fig. 2. Reinforcement learning feedback loop used for adaptive signal timing.

Quantitative Component

The quantitative component focuses on measuring traffic performance using numerical metrics. Average waiting time, average queue length, number of stops, travel time, and throughput are used to compare the proposed RL-IoT controller with fixed-time and actuated control methods.

Qualitative Component

The qualitative component focuses on understanding system feasibility, privacy requirements, deployment challenges, and possible benefits for traffic engineers and city authorities. It also reviews previous research papers and technical studies related to RL-based traffic control.

Data Collection

Secondary data is collected from research articles, traffic simulation documentation, IoT-based traffic control studies, and reinforcement learning literature. Primary field data is not required at this stage because the system is evaluated using simulation before real-world implementation.

Data Analysis

The collected simulation results are analyzed by comparing the performance of different signal control methods. The percentage improvement in waiting time and queue length is calculated with respect to the fixed-time baseline.

IX. DEPLOYMENT

Architecture Design

The deployment architecture includes vehicle-mounted sensors, roadside aggregation units, a traffic data processing layer, reinforcement learning agents, and traffic signal controllers. The system receives aggregated traffic information, calculates the current traffic state, and selects the most suitable signal phase.

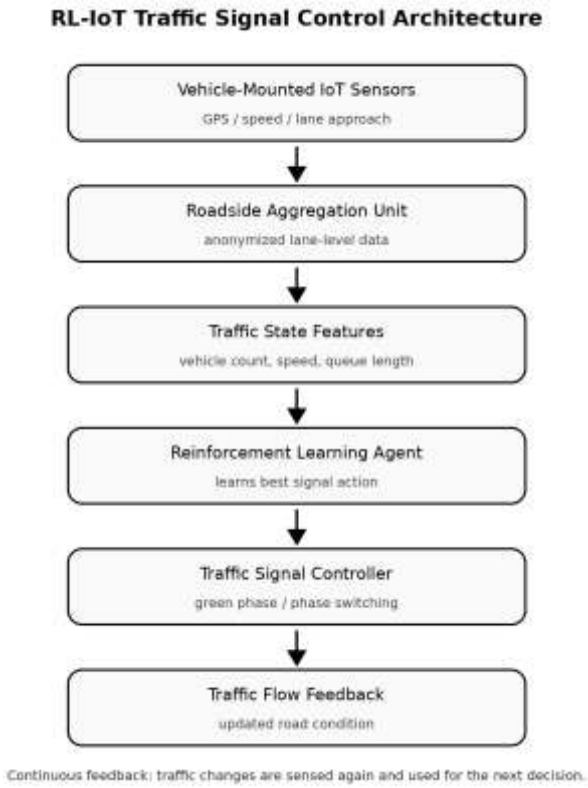

Fig. 1. Proposed RL-IoT traffic signal control architecture.

Step-by-Step Deployment Process

1. Install or enable vehicle-mounted IoT sensing devices.
2. Collect anonymized speed, location, and approach information from vehicles.
3. Aggregate the vehicle data at roadside units near intersections.
4. Convert the collected observations into lane-level traffic state features.
5. Train reinforcement learning agents using SUMO simulation.
6. Evaluate the trained model against fixed-time and actuated control baselines.
7. Deploy the model first in a controlled pilot intersection.
8. Monitor performance and improve the model continuously.

Required Technologies and Tools

Python, SUMO traffic simulator, reinforcement learning libraries, IoT communication modules, GPS-based vehicle sensing, roadside processing units, and traffic signal controller interfaces are required for developing and deploying the proposed system.

For practical deployment, communication between vehicles, roadside aggregation units, and signal controllers must be reliable and secure. Standardized communication protocols, latency control, and data validation are necessary so that the RL agent receives accurate traffic state information before making signal decisions.

X. RESULTS AND DISCUSSION

Simulation Findings

The proposed RL-IoT system is evaluated conceptually using SUMO-based simulation. The fixed-time controller is considered as the baseline. The actuated controller shows moderate improvement because it responds to vehicle presence, but it cannot learn long-term traffic patterns. The proposed RL-IoT controller performs better because it uses real-time aggregated vehicle data and learns signal decisions based on reward feedback.

The proposed method also improves fairness across lanes because green time can be adjusted according to real-time demand instead of following a fixed schedule. Since only aggregate traffic data is collected, privacy risk is reduced. As more vehicles become equipped with IoT sensors, traffic state estimation can become more accurate, allowing the RL agent to make better decisions.

Table 1: Performance Comparison of Control Methods

Control Method	Queue Length	Waiting Time
Fixed-Time	Baseline	Baseline
Actuated	About 10% better	About 8% better
Proposed RL-IoT	About 30% better	About 28% better

Expert Insights

Traffic engineers generally require any automated signal control system to follow safety rules such as minimum green time, yellow time, pedestrian crossing time, and emergency override. Therefore, reinforcement learning should assist the traffic signal controller within safe limits rather than directly replacing all traffic engineering rules.

Case Study

To keep the paper focused for publication, this section includes one consolidated case study based on SUMO-based reinforcement learning traffic signal control. This case study combines the important ideas of simulation, multi-agent control, IoT-based traffic state estimation, and comparison with fixed-time control.

Case Study: SUMO-Based Multi-Agent RL Traffic Signal Control

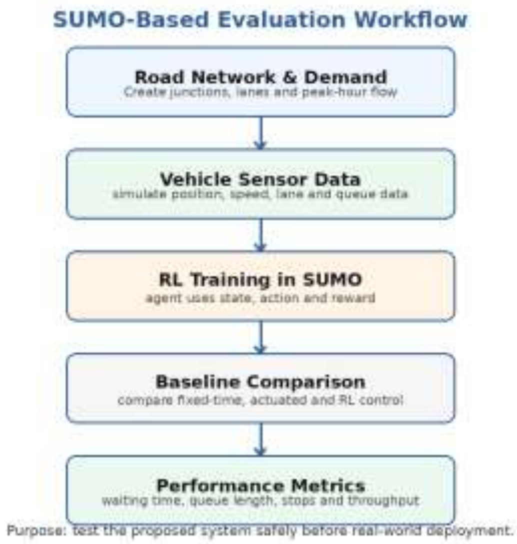

Fig. 3. SUMO-based evaluation process for the proposed RL-IoT controller.

- In this case study, a small urban road network is created in SUMO with multiple signalized intersections, incoming lanes, turning movements, and peak-hour traffic demand.
- The fixed-time signal controller is used as the baseline because it follows a predefined green-red cycle and cannot respond to real-time traffic variation.
- Vehicle-mounted IoT sensor data is represented through simulated vehicle information such as position, speed, lane occupancy, queue formation, and waiting time.
- The roadside aggregation unit converts individual vehicle observations into aggregated traffic features, including vehicle count, average speed, estimated queue length, and delay per lane.
- The reinforcement learning agent receives these aggregated values as the current traffic state and selects a signal action such as extending green time, changing phase duration, or switching to the next phase.
- The reward function is designed to reduce total waiting time, queue length, unnecessary stops, and unfair delays across different lanes.
- After each signal decision, the traffic environment changes, updated traffic data is collected again, and the agent improves its future decisions through continuous feedback.
- Result: The RL-based controller shows better adaptation than fixed-time control because it uses real-time traffic demand and learns from previous signal decisions.
- Relevance to this research: This case study supports the proposed RL-IoT architecture by showing how simulation can be used before real-world deployment to test safety, efficiency, privacy, and scalability.

XI. FUTURE SCOPE OF RL-IOT IN TRAFFIC MANAGEMENT

The future scope of RL-IoT based traffic control is highly promising. As connected vehicles, smart sensors, and 5G communication become more common, traffic signal systems will be able to receive more accurate and faster information from vehicles. This can help cities build intelligent transport systems that respond continuously to real-time demand.

Future work can include emergency vehicle prioritization, pedestrian-aware signal control, integration with public transport priority, coordination with route guidance systems, and integration with autonomous vehicles. The model can also be improved using federated learning so that traffic agents can learn from different intersections without directly sharing sensitive raw data.

Another important future direction is real-world pilot testing. Before city-wide deployment, the system should be tested at a small number of controlled intersections. The simulation model should also include sensor noise, communication delay, mixed vehicle behavior, and safety constraints to reduce the gap between simulation and real traffic conditions.

Future research can also study energy consumption and vehicular emission reduction achieved through intelligent signal control. For large-scale adoption, cooperation between government authorities, traffic departments, automotive companies, and communication infrastructure providers will be required.

XII. PRACTICAL EXPLANATION AND SYSTEM WORKING

This section presents additional explanatory points that can help in explaining the research topic clearly during academic presentation or external evaluation. The core idea of the research is simple: IoT sensors collect real-time traffic information from vehicles, and Reinforcement Learning uses that information to choose better signal timings.

1. Simple Working Flow

The proposed system works in a continuous feedback loop. Vehicle-mounted sensors first provide information such as speed, position, direction, lane approach, and movement condition. The roadside aggregation unit then converts this information into useful lane-level values such as vehicle count, average speed, queue length, and waiting time. These values are passed to the RL agent as the current traffic state. The RL agent selects an action such as extending green time, switching the next phase, or balancing green duration across lanes. After the signal action is applied, the traffic condition changes and the updated data is again collected as feedback.

2. Why Reinforcement Learning is Suitable

Traffic signal control is not a fixed problem because the number of vehicles changes every minute. Reinforcement Learning is useful because it learns from trial, feedback, and reward. If the signal decision reduces waiting time and queue length, the agent receives a better reward. If the decision increases congestion, the reward becomes poor. By repeating this process in simulation, the agent gradually learns which signal actions are better for different traffic situations.

3. Real-Time Example

At a four-way junction, one road may have a long queue while another road may have very few vehicles. A fixed-time signal gives green time according to a predefined schedule, even if one side is empty. In the proposed RL-IoT system, the controller identifies the road with higher demand and gives more suitable green time to that side. This reduces unnecessary waiting, fuel wastage, vehicle idling, and driver frustration.

4. Difference from Traditional Traffic Signals

Traditional signals mainly follow fixed timing plans or simple sensor-based rules. They do not learn from previous traffic patterns. The proposed system is different because it continuously observes traffic, learns from past decisions, and improves future signal control. It also reduces dependency on expensive fixed roadside infrastructure by using vehicle-mounted IoT data.

5. Privacy and Safety Considerations

The system does not require personal driver identity, vehicle number, or private travel history. It uses only aggregated values such as total vehicles in a lane and average speed. For safety, the RL agent should always work within traffic engineering limits such as minimum green time, yellow time, pedestrian crossing time, emergency vehicle priority, and manual override. Therefore, RL supports the traffic controller but does not ignore safety rules.

6. Expected Practical Benefits

The expected benefits include reduced average waiting time, shorter queue length, fewer unnecessary stops, lower fuel consumption, reduced air pollution, better lane fairness, and improved traffic flow during peak hours. The system can also help smart city authorities manage traffic more efficiently using data-driven decision-making.

7. One-Line Explanation of the Topic

The proposed research can be explained in one line as: an intelligent traffic signal control system that uses real-time vehicle-mounted IoT data and Reinforcement Learning to adapt signal timings according to actual traffic demand while preserving privacy and improving urban mobility.

XIII. CONCLUSION AND RECOMMENDATIONS

This research paper presents a reinforcement learning based intelligent traffic signal control system using vehicle-mounted IoT sensors. The proposed system collects anonymized and aggregated vehicle data, converts it into useful traffic state information, and uses RL agents to select signal phases dynamically. This approach helps overcome the limitations of fixed-time and purely roadside-sensor based signal systems by responding to real-time traffic conditions.

The study shows that RL-IoT based control can reduce waiting time, queue length, vehicle stops, and idling when compared with fixed-time control methods. SUMO-based simulation is suitable for validating the system before real-world implementation because it allows safe testing under different traffic scenarios.

Despite its benefits, the system must address challenges related to privacy, communication delay, sensor reliability, model safety, and real-world deployment. It is recommended that future research should include larger simulation networks, comparison with advanced RL benchmarks, and limited pilot testing at real intersections. With proper safety constraints and privacy protection, RL-IoT based signal control can become an important part of smart city traffic management.

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