AI-Powered Smart Cities: Optimizing Traffic Signal Control with Cooperative Multi-Agent Reinforcement Learning

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Abstract

As urbanization accelerates, traffic congestion has become a major challenge in smart cities. Traditional traffic management systems, which rely on static or reactive algorithms, struggle to adapt to dynamic urban environments. Artificial Intelligence (AI), particularly Cooperative Multi-Agent Reinforcement Learning (MARL), offers a novel solution to optimizing traffic signal control. By treating traffic lights as intelligent agents that learn and collaborate in real-time, MARL-based systems can enhance traffic efficiency, minimize congestion, and improve sustainability. This paper explores the role of AI in smart city traffic management, discusses the advantages of MARL over traditional methods, and examines real-world applications. Additionally, it highlights the challenges and future research directions in implementing MARL for traffic signal control.

Keywords : Smart Cities, Traffic Signal Control, Reinforcement Learning, Multi-Agent Systems, Intelligent Transportation Systems.

Introduction

As urban populations grow and cities become more congested, traditional traffic management systems struggle to meet the increasing demand for smoother, more efficient traffic flow. The concept of smart cities has emerged to address these challenges, integrating advanced technologies to enhance urban living. A critical area where Artificial Intelligence (AI) is making a substantial impact is traffic signal control. AI technologies, particularly Cooperative Multi-Agent Reinforcement Learning (MARL), are proving to be transformative in optimizing the management of traffic signals across urban road networks. By using AI to enable traffic signals to make real-time decisions based on surrounding conditions, cities can reduce traffic congestion, minimize delays, and improve the overall transportation experience.

Smart Cities

Smart cities use digital technologies to improve the efficiency of urban services such as transportation, energy, healthcare, and waste management. These cities rely heavily on interconnected systems powered by sensors, AI, and big data to monitor and optimize the use of resources. Traffic management is one of the most critical services in a smart city because it directly influences a city's overall functionality. AI systems can analyze traffic patterns, adapt to changing conditions, and make autonomous decisions to ensure that vehicles move as smoothly as possible [1]. Fig1 shows a view of a smart city.

Figure (1) smart cities

Traditional Traffic Signal Systems and Their Limitations

Traditional traffic signal systems are often static, programmed with fixed timings or simple reactive algorithms that control the light changes. These systems are typically designed based on historical traffic data, meaning they do not adapt well to sudden changes, such as road accidents, unexpected congestion, or new traffic patterns. As a result, drivers often face long waiting times at intersections, which leads to unnecessary fuel consumption, increased pollution, and frustrated commuters. The limitations of these traditional systems highlight the need for more intelligent, flexible, and adaptive solutions, such as those powered by AI [2].

Reinforcement Learning in Traffic Signal Control

Reinforcement Learning (RL) is a machine learning technique where an agent (in this case, a traffic signal) learns to make decisions by interacting with its environment. The agent performs actions, observes the outcomes, and receives feedback in the form of rewards or penalties. Over time, the agent learns the optimal strategy to maximize long-term rewards, such as improving traffic flow or reducing waiting times. In traffic signal control, RL allows a traffic signal to learn when to change its lights based on real-time conditions. For example, if a traffic signal detects a high volume of cars waiting at an intersection, it may extend the green light to clear the traffic. If the volume of cars is low, it can shorten the green light duration. By using RL, traffic signals can become more adaptive, improving the overall flow of traffic and reducing congestion [3].

Cooperative Multi-Agent Reinforcement Learning (MARL)

While individual RL models can optimize a single traffic signal, real urban traffic systems consist of multiple intersections that need to work together to optimize the entire network. This is where Cooperative Multi-Agent Reinforcement Learning (MARL) comes into play. A graphical view of this system is shown in Fig2.

In MARL, multiple traffic signals are treated as independent agents that collaborate with each other to improve the efficiency of the entire traffic system. Each agent (traffic signal) learns its own optimal policies (such as when to change its light) based not only on local conditions (like traffic volume) but also by considering the actions and states of neighboring agents. By communicating and sharing information about the traffic conditions at various intersections, agents can make more informed decisions, resulting in smoother traffic flow throughout the city [4].

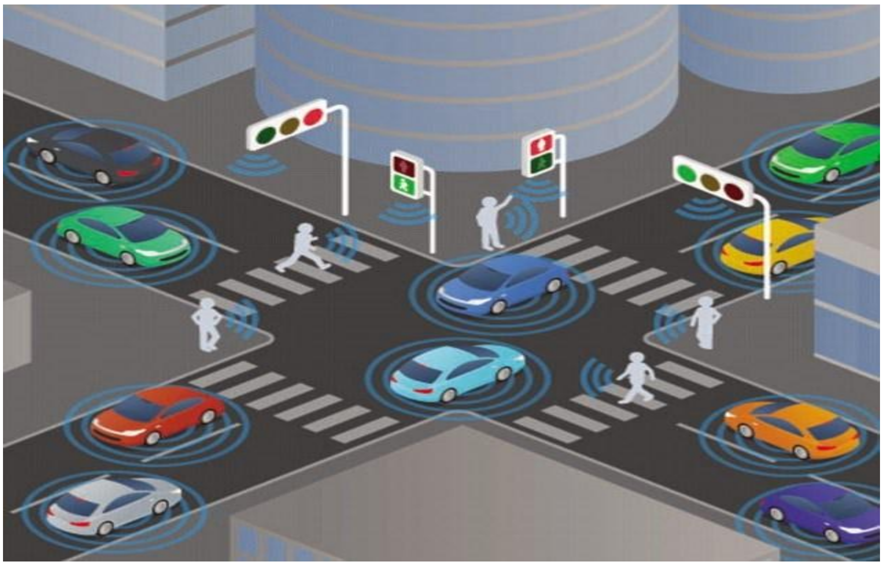

Figure (2) Cooperative Multi-Agent Reinforcement Learning (MARL)

Advantages of MARL in Traffic Signal Control

Some of the advantages of Cooperative Multi-Agent Reinforcement Learning are as follows:

- **Dynamic Adaptation:** Unlike traditional traffic signal systems, which follow fixed rules, MARL-based systems can adapt to real-time traffic conditions [5].
- **Global Optimization:** By working together, traffic signals can improve the overall efficiency of the network, reducing congestion at specific intersections and balancing traffic flow across the city [6].
- **Scalability:** MARL systems can be scaled to handle large cities with many intersections [7].
- **Energy Efficiency and Sustainability:** By reducing waiting times and improving the flow of vehicles, MARL can help reduce fuel consumption and lower emissions.
- **ower Fuel Consumption** – Less idling and smoother traffic flow reduce fuel waste, promoting sustainability.
- **Decreased Greenhouse Gas Emissions** – Optimized traffic flow leads to lower carbon emissions and improved air quality.
- **Improved Public Transport Efficiency** – MARL can prioritize buses and emergency vehicles, enhancing public transit operations.
- **Better Coordination Between Intersections** – Agents communicate to create a synchronized traffic management system.

Techniques, challenges, and solutions for AI-based traffic signal control systems are shown in Table 1.

Table1. AI-Based Traffic Signal Control: Techniques, Challenges, and Solutions

Ref	Year	Techniques Used	Solutions	Challenges	Methodology
[1]	2024	MARL, CNN-based Feature Extraction	Computational Efficiency, Optimal Traffic Flowa	Scalability, High Initial Setup	Scalable feature map, Real-time optimization
[2]	2024	POMDP, Multi-Agent Coordination	Handle Computational Complexity, Real-time Decision Making	Dynamic Environment, Unexpected Congestion	Use Dynamic Uncertainty Modeling
[3]	2024	Deep Q-Network (DQN), PPO, Reward Shaping	Synchronization of Traffic Signals, Adaptive Policies	Computational Cost, Limited to Complex Traffic	Efficient for Training: RL, Dynamic Decision Making
[4]	2024	NMPC, MARL, Graph Neural Networks (GNN)	Reduce Computational Cost, Stable Decision-Making	Dynamic Traffic Flow, Non-stationary Environment	Multi-Agent Coordination for Traffic Optimization
[5]	2024	MPC+APF, Transformer-based Learning	Smooth Traffic Flow, Reduced Computational Burden	Scalability, Real-Time Adaptation	Use Scalable APF, Enhance Prediction Models
[6]	2024	QP, APF+MPC+ESP P	Handling Local Minima, Collision Avoidance in High-Speed Traffic	Computational Complexity, Real-Time Constraints	Optimize RL Policies, Extend Decision-making Capabilities
[10]	2024	MPEC+MINLP, Distributed Learning	Scalability, Confidence in Decision-Making	Real-Time Processing, Uncertainty in Vehicle Motion	Parallel Computing for Dynamic Traffic Signal Control
[11]	2024	NLP, Graph Attention Networks (GAT)	Trajectory Smoothness, Real-time Adaptability	Dynamic Traffic, High Computational Demand	Use Motion Prediction Methods, Parallel Computation
[12]	2024	PhERS+, DDPG+, HLER+, DRL-based Controller	Scalability, Efficiency, Real-time Traffic Optimization	Optimal Pheromone Parameters, Traffic Adaptability	Enhanced Reinforcement Learning Strategies
[13]	2024	LSTM, Evolutionary PSO, Neuromuscular Dynamics	Handling Complex Traffic Patterns, Driver Behavior Prediction	Real-world Deployment, Scalability	Extend Scenarios, Use Lightweight AI Models
[14]	2024	Bezier and Circular Curves, MPC	Path Optimization, Smooth and Safe Traffic Routing	Advanced Traffic Flow Forecasting	Learning-based Obstacle and Traffic Flow Prediction

Case Studies and Real-World Applications

Several studies have demonstrated the effectiveness of MARL in optimizing urban traffic systems. For example, research by Zang et al. (2021) introduced **MetaLight**, a value-based MARL framework that significantly improved urban traffic efficiency [8]. Another study by Wei et al. (2019) proposed **IntelliLight**, an RL-based adaptive traffic signal control system that optimized real-time decisions for urban intersections [9].

Challenges and Considerations

Challenges and Considerations for MARL systems are as follows: (And also in Table 2).

- **Data Collection:** Accurate, real-time data is crucial for the effectiveness of MARL systems [10].
- **Computational Complexity:** Training MARL models requires significant computational resources.
- **Integration with Existing Infrastructure:** Integrating MARL-based systems into existing traffic control infrastructure may require significant upgrades.
- **Robustness:** Ensuring that MARL systems can handle unexpected events is critical for their successful deployment.
- **High Computational Demand** – Training MARL models requires extensive computational resources, making real-time decision-making complex.
- **Scalability Issues** – Large urban traffic networks with multiple intersections require efficient coordination, which becomes increasingly complex.
- **Data Quality and Availability** – Real-time AI models rely on accurate, high-quality traffic data, which may not always be available.
- **Communication Latency** – Traffic signals must exchange information quickly; network delays can affect decision-making.
- **Dynamic and Uncertain Traffic Conditions** – Unexpected road incidents (accidents, weather changes) disrupt pre-learned AI strategies.
- **Adversarial Attacks and Security Risks** – AI-based systems are vulnerable to cyberattacks, leading to traffic disruptions.
- **Ethical and Regulatory Concerns** – Implementing AI in public infrastructure raises concerns about fairness, transparency, and accountability.

Table 2. Techniques, Solutions, Challenges, and Future Directions

Technique	Key Solutions	Challenges	Future Directions
MARL-based Traffic Signal Control	- Real-time adaptive control based on traffic conditions.	- High computational demands for model training.	- Efficient parallel computing techniques for real-time updates.
Value-based MARL (MetaLight)	- Improved traffic efficiency through collaborative agent learning.	- Scalability issues in large urban networks.	- Further improvement of scalability and network coordination.
Deep Q-Network (DQN) & PPO	- Dynamic decision-making for real-time signal adjustments.	- High computational cost for training deep reinforcement models.	- Development of lightweight and faster models for urban deployment.
Cooperative Multi-Agent Reinforcement Learning	- Global optimization by enabling communication between traffic signals.	- Handling dynamic and uncertain traffic conditions.	- Integrating real-time data from IoT devices to enhance responsiveness.
Graph Neural Networks (GNN) for Traffic Optimization	- Optimizing traffic flow and reducing congestion across interconnected intersections.	- Real-time data collection and quality issues.	- Developing more efficient data collection and processing methods.
Adaptive Traffic Signal Policies (IntelliLight)	- Adaptive real-time decision-making in response to traffic volume changes.	- Integration with existing legacy infrastructure.	- Transitioning from experimental to widespread real-world deployment.
Model Predictive Control (MPC) with MARL	- Smoother traffic flow and reduced congestion at high-traffic intersections.	- Complexity of large-scale coordination across multiple agents.	- Advancements in coordination techniques for complex intersections.

Conclusion

The integration of Cooperative Multi-Agent Reinforcement Learning (MARL) in traffic signal control represents a revolutionary approach to managing urban traffic in smart cities. By enabling traffic signals to collaborate and make data-driven decisions, cities can achieve more efficient traffic flow, reduced congestion, and improved sustainability. While challenges such as data requirements and computational complexity remain, ongoing research and advancements in AI hold promise for the widespread adoption of MARL-based systems.

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Nomenclature

- **AI**: Artificial Intelligence
- **MARL**: Multi-Agent Reinforcement Learning
- **RL**: Reinforcement Learning
- **MPC**: Model Predictive Control
- **DQN**: Deep Q-Network
- **PPO**: Proximal Policy Optimization
- **GNN**: Graph Neural Network
- **CNN**: Convolutional Neural Network

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List of Symbols

- S: State space of the traffic signal system
- A: Action space of traffic signal agents (e.g., green, red, yellow lights)