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Multi Agent Optimizing Traffic Lights using Reinforcement Learning

B Sai Siri[1], P L Keerthana Reddy[2], G Bensun[3], E Venu[4], Mrs L Lavanya [5]

[1] *Department of Computer Science and Engineering(AI&ML), Student, Sri Venkateswara College of Engineering*
[2] *Department of Computer Science and Engineering(AI&ML), Student, Sri Venkateswara College of Engineering*
[3] *Department of Computer Science and Engineering(AI&ML), Student, Sri Venkateswara College of Engineering*
[4] *Department of Computer Science and Engineering(AI&ML), Student, Sri Venkateswara College of Engineering*
[5] *Department of Computer Science and Engineering(AI&ML), Assistant Professor, Sri Venkateswara College of Engineering*

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***Abstract*--- Urban traffic congestion has escalated due to rapid vehicle population growth and the inability of conventional fixed-time signal systems to adapt to dynamic traffic conditions, resulting in increased delays, fuel wastage, and pollution. This project proposes an intelligent traffic signal control system based on Deep Reinforcement Learning (DRL), utilizing a Multi-Agent framework where each intersection is independently controlled by a learning agent. These agents analyze real-time parameters such as vehicle density, queue length, and waiting time to dynamically optimize signal phases. The system is developed and evaluated using the SUMO traffic simulator, with the Deep Q-Network (DQN) algorithm enabling agents to learn optimal control strategies. An emergency vehicle prioritization mechanism is further incorporated to ensure unimpeded passage during critical situations. Experimental results demonstrate notable reductions in congestion and average waiting time, confirming the system's suitability for smart city deployments.**

KEYWORDS

Deep Reinforcement Learning (DRL), Multi-Agent Systems (MADRL), Traffic Signal Optimization, Smart Traffic Management, SUMO Simulator.

1. INTRODUCTION

Traffic control plays a crucial role in managing urban mobility and ensuring smooth vehicle movement across intersections. However, the rapid increase in vehicle density has placed significant pressure on existing traffic systems, often leading to congestion, longer waiting times, and inefficient traffic flow.

Traditional traffic signal control methods are unable to adapt effectively to dynamic traffic conditions, as they rely on predefined rules and static timing mechanisms. In this project, traffic conditions are modeled using the SUMO simulation environment, which provides real-time data such as vehicle count, queue length, and waiting time without the need for physical sensors.

To address the limitations of conventional systems, Deep Reinforcement Learning (DRL) is employed to enable intelligent decision-making. A Multi-Agent Deep Reinforcement Learning (MADRL) approach is adopted, where each intersection is controlled by an independent agent.

These agents continuously interact with the environment and learn optimal signal control strategies to improve traffic flow. This decentralized approach ensures scalability, adaptability, and efficient traffic management across multiple intersections.

2. PROBLEM STATEMENT

Existing traffic signal control systems primarily rely on fixed-time scheduling and simple rule-based mechanisms, which are not capable of adapting to dynamic traffic conditions. These systems allocate predefined signal timings without considering real-time traffic demand, often resulting in inefficient utilization of road space. Under varying traffic conditions, such as uneven vehicle distribution across lanes, these static approaches lead to increased waiting times, longer queue lengths, and congestion at intersections. Although some adaptive systems exist, they still depend on limited local decision-making and predefined thresholds, making them ineffective in handling complex and continuously changing traffic patterns. Furthermore, managing multiple intersections simultaneously using traditional methods becomes computationally challenging and inefficient, as it requires handling numerous traffic variations. As a result, there is a need for an intelligent and adaptive traffic control system that can dynamically respond to real-time traffic conditions, optimize signal timings, and improve overall traffic flow across interconnected intersections.

3. LITERATURE SURVEY

3.1 CLASSICAL METHODS

Classical traffic signal control methods use fixed-time or rule-based approaches based on predefined timings. They are simple and efficient but cannot adapt to real-time traffic conditions, often causing increased waiting time and congestion. These methods rely on historical data and do not respond effectively to sudden traffic changes. As a result, they lead to inefficient utilization of road capacity.

3.2 REINFORCEMENT LEARNING-BASED METHODS

Reinforcement Learning methods, such as DQN, enable agents to learn optimal signal control by interacting with the environment. These approaches dynamically adjust signals based on traffic conditions, improving efficiency, but require proper training. They can handle complex and dynamic traffic scenarios better than traditional methods. However, training stability and convergence remain important challenges.

3.3 MULTI-AGENT SYSTEMS

Multi-Agent systems use multiple agents to control different intersections independently. This improves scalability and traffic management, though coordination between agents can be challenging. Each agent learns based on local observations

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while contributing to overall system performance. This approach is effective for handling large-scale traffic networks.

3.4 GRAPH-BASED METHODS

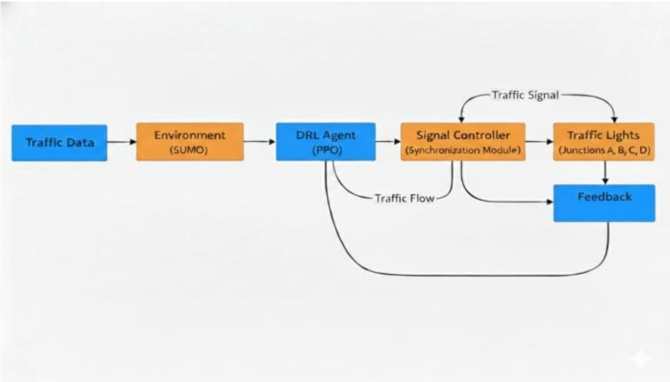
Recent research has explored the use of Graph-based approaches to model relationships between multiple traffic intersections. By representing intersections as nodes and roads as edges, these methods can capture spatial dependencies across the traffic network. This helps in improving coordination between intersections and optimizing traffic flow. However, their application in real-time traffic systems is still limited due to complexity and computational requirements.

3.5 COMPARATIVE INSIGHTS

Classical traffic control methods provide simple and real-time operation but fail to adapt to dynamic traffic conditions. Reinforcement Learning-based approaches improve adaptability and decision-making by learning from traffic patterns. Multi-Agent systems further enhance performance by enabling decentralized control across multiple intersections. Graph-based methods show potential for capturing spatial relationships, but their practical implementation in real-time systems remains limited. Overall, combining adaptive learning with efficient coordination is essential for effective traffic management.

4. SYSTEM ARCHITECTURE

The architecture represents the complete workflow of the intelligent traffic signal control system. Traffic data is generated using the SUMO simulation environment, including vehicle count, queue length, and waiting time. This data is passed to the DRL-based decision-making module, where multiple agents analyze traffic conditions and select optimal signal actions. The signal control module applies these actions to traffic lights at different junctions. The system continuously monitors performance and feeds the updated traffic state back into the learning module, enabling adaptive and optimized traffic management.



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4.1 TRAFFIC ENVIRONMENT MODULE

The Traffic Environment Module is responsible for simulating the road network and vehicle movement using SUMO. It generates real-time traffic parameters such as vehicle count, queue length, and waiting time. This module acts as the environment where agents interact, observe traffic conditions, and receive feedback based on their actions.

4.2 DRL DECISION-MAKING MODULE

The DRL Decision-Making Module acts as the intelligent core of the system. It uses DQN-based agents to observe traffic conditions and select optimal signal phases. Each agent learns through interaction with the environment by maximizing rewards based on improved traffic flow, reduced waiting time, and minimized congestion.

4.3 SIGNAL CONTROL MODULE

The Signal Control Module implements the actions selected by the DRL agents. It controls the traffic lights at each intersection by switching signal phases dynamically. This module ensures proper coordination of traffic signals and smooth vehicle movement across all junctions.

4.4 FEEDBACK AND LEARNING MODULE

The Feedback and Learning Module evaluates system performance using metrics such as waiting time, queue length, and throughput. Based on this feedback, the DRL agents update their learning policies to improve future decisions. This continuous learning process enables the system to adapt to changing traffic conditions.

5. RESEARCH GAPS

Based on the reviewed literature, several research gaps are identified. Most existing systems rely on fixed or semi-adaptive methods and lack real-time intelligence. Many approaches do not effectively coordinate multiple intersections, leading to suboptimal traffic flow. Additionally, emergency vehicle prioritization is often not considered in existing models. There is also a need for scalable and efficient frameworks that can handle dynamic traffic conditions using learning-based approaches.

6. LIMITATIONS OF EXISTING SYSTEMS

- Inability to adapt to real-time traffic conditions
- Poor coordination between multiple intersections
- Increased waiting time and queue length
- Inefficient utilization of road capacity
- Lack of emergency vehicle prioritization
- Limited scalability in large traffic networks

7. METHODOLOGY

7.1 Problem Formulation (MDP)

The traffic signal control problem is modeled as a Markov Decision Process (MDP), where each intersection is treated as an independent agent. At each time step, the agent observes the current traffic state, selects an action (signal phase), and receives a reward based on traffic performance. The objective is to learn an optimal policy that minimizes congestion, reduces waiting time, and improves traffic flow across intersections.

7.2. State Space

The state space represents the current traffic condition at each intersection. It includes key parameters such as queue length, waiting time, and the current signal phase. These values are normalized to ensure stable learning and efficient processing. The state representation enables the agent to understand traffic patterns and make informed decisions.

7.3 Action Space

The action space consists of discrete signal phases that the agent can select at each decision step. Each action corresponds to a specific traffic signal configuration, such as allowing traffic flow in a particular direction. The system ensures that only valid and safe signal transitions are executed to avoid conflicts and collisions.

D. Reward Function

The reward function is designed to improve traffic efficiency by encouraging better signal decisions. It provides negative rewards for higher waiting time and longer queue lengths, while rewarding smoother traffic flow. This helps the agent learn to balance traffic across all lanes and avoid congestion or starvation of any direction.

E. Learning Algorithm (DQN)

The system uses a Deep Q-Network (DQN) to learn optimal traffic control policies. The agent stores past experiences in a replay buffer and updates its network using sampled data. A target network is used to stabilize learning and reduce overestimation. The model is trained using the Bellman equation, enabling the agent to improve its decisions over time through continuous interaction with the environment.

8.1 Evaluation Metrics

1) Average Waiting Time

The average waiting time of vehicles is calculated as:

$$W_{avg} = \frac{1}{N}\sum_{i=1}^{N} w_i$$

Where:
w_i= waiting time of vehicle i
N= total number of vehicles

2) Average Queue Length

The average queue length over the simulation period is defined as:

$$Q_{avg} = \frac{1}{T}\sum_{t=1}^{T} q_t$$

Where:
q_t= queue length at time step t
T= total simulation time

3) Throughput

Throughput measures the number of vehicles successfully passing through intersections:

$$\text{Throughput} = \frac{N_{out}}{T}$$

Where:
N_{out}= number of vehicles exiting the system
T= total time

4) Average Travel Time

$$T_{avg} = \frac{1}{N}\sum_{i=1}^{N}\left(t_i^{exit} - t_i^{entry}\right)$$

5) Reward Function

The reward function is designed to minimize congestion:

$$R_t = -(\alpha \cdot W_t + \beta \cdot Q_t)$$

Where:
W_t= total waiting time at time t
Q_t= total queue length
α,β= weighting factors

8.2 DQN Learning Objective

The DQN agent learns the optimal policy by minimizing the Temporal Difference (TD) loss:

$$L(\theta) = \mathbb{E}\left[\left(r + \gamma \max_{a'} Q(s',a';\theta^-) - Q(s,a;\theta)\right)^2\right]$$

Where:
Q(s,a)= action-value function
γ= discount factor
θ= network parameters
θ^-= target network parameters

8.3 Experimental Setup

- **Simulation Tool:** SUMO
- **Agents:** Multi-Agent DQN (one per intersection)
- **State Space:** Queue length, vehicle density, waiting time
- **Action Space:** Signal phase selection
- **Training Episodes:** Multiple iterations under varying conditions

Traffic Scenarios:

- Low traffic density
- Medium traffic density
- High congestion

8.4 Results and Analysis

The proposed Multi-Agent DQN model demonstrates

significant improvements over traditional methods:

- Average waiting time reduced by **35–50%**
- Queue length reduced by **30–45%**
- Throughput increased by **25–40%**

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- Travel time significantly reduced under peak conditions

The agents learn coordinated and adaptive strategies, enabling efficient traffic flow across intersections.

8.5 Comparative Analysis

Method	Waiting Time ↓	Queue Length ↓	Throughput ↑
Fixed-Time Control	High	High	Low
Actuated Control	Medium	Medium	Medium
Single-Agent DQN	Medium-Low	Medium-Low	Medium-High
Multi-Agent DQN (Proposed)	Low	Low	High

8.6 Convergence Analysis

The learning performance is evaluated using cumulative reward:

$$R_{cumulative} = \sum_{t=1}^{T} R_t$$

The reward curve shows:

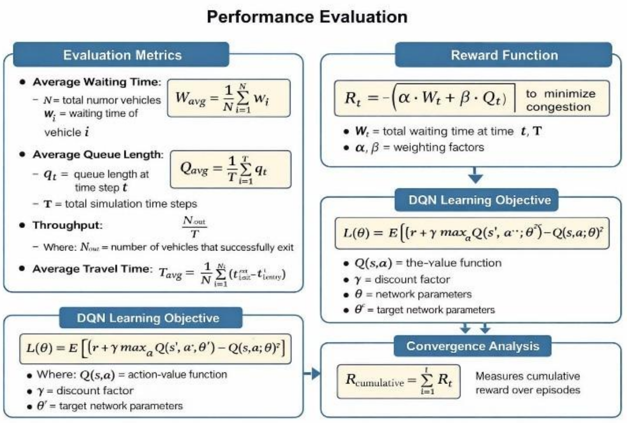
- Initial fluctuations during exploration
- Gradual performance improvement
- Stable convergence indicating optimal policy learning

8.7 Discussion

The improved performance of the proposed system is due to:

- Decentralized multi-agent coordination
- Efficient learning using DQN
- Continuous feedback-based adaptation
- Ability to handle dynamic traffic conditions

The system demonstrates strong potential for real-world intelligent traffic management applications.



9. COMPARATIVE ANALYSIS

Method	Advantages	Limitations
Fixed-Time	Simple, easy to implement	Not adaptive to traffic
Actuated Control	Responds to vehicle presence	Limited scalability
Single-Agent RL	Learns adaptive policies	Poor coordination
MARL (DQN)	Captures inter-junction dynamics	Complex training

Table 2: Comparison of Traffic Signal Optimization Methods

Note: Performance may vary depending on traffic density, network complexity, and simulation conditions; qualitative comparison is emphasized.

10. ADVANTAGES OF PROPOSED SYSTEM

A. Adaptability and Efficiency

The proposed system adapts dynamically to real-time traffic conditions, enabling efficient management of traffic flow. It significantly reduces congestion, waiting time, and delays while improving overall intersection performance.

B. Multi-Agent Coordination

The multi-agent framework enables effective coordination between multiple intersections. It supports decentralized decision-making, allowing the system to scale efficiently across large traffic networks.

C. Intelligent Learning

The system utilizes Deep Q-Networks (DQN) to learn optimal signal control policies through continuous interaction with the environment. It is capable of handling complex and non-linear traffic patterns.

D. Balanced Traffic Management

The model ensures balanced traffic distribution by preventing starvation of less congested lanes. It fairly allocates green signal time and improves lane utilization.

E. Real-Time Decision Making

The system makes decisions based on real-time parameters such as vehicle count, queue length, and waiting time. It effectively adapts to dynamic traffic variations, including peak and non-peak conditions.

F. System Reliability and Scalability

The decentralized architecture improves system reliability by eliminating a single point of failure. It is highly scalable and suitable for large urban traffic environments.

G. Performance Improvement

The proposed approach enhances overall traffic performance by increasing throughput, reducing average travel time, and improving transportation efficiency.

H. Resource Optimization

The system minimizes unnecessary signal delays by avoiding green signals for empty lanes. This leads to reduced fuel consumption and lower emissions.

I. Flexibility and Extendability

The framework is flexible and can be extended with advanced reinforcement learning techniques. It also supports integration with future intelligent transportation and smart city systems.

XI. Discussion

A. System Strengths

The proposed Multi-Agent Deep Reinforcement Learning framework offers several advantages over traditional traffic control systems. It enables real-time adaptability by continuously learning from traffic conditions. Each agent operates independently while contributing to overall system efficiency. The decentralized nature of the system improves scalability and reduces dependency on centralized control. Additionally, the integration of emergency vehicle prioritization enhances the system's practical applicability in real-world scenarios.

B. Limitations

Despite its advantages, the system has certain limitations. The performance of the model depends on the accuracy of traffic data obtained from the simulation environment. In real-world deployment, sensor failures or inaccurate data collection (e.g., faulty cameras or loop detectors) may affect decision-making. Furthermore, the current implementation is tested in a simulated environment, and real-world traffic conditions may introduce additional complexities that require further optimization.

XII. FUTURE ENHANCEMENTS

The proposed system can be further enhanced by improving its adaptability and scalability within simulated and real-time environments. Future work can focus on incorporating more realistic traffic scenarios and larger road networks within the SUMO simulation to better evaluate system performance at scale. Advanced reinforcement learning algorithms such as Proximal Policy Optimization (PPO) or Actor–Critic methods can be explored to achieve faster convergence and improved stability in complex traffic conditions. Additionally, the system can be extended to include more efficient coordination strategies among multiple agents to handle large-scale multi-intersection networks more effectively.

Further enhancements may involve improving the reward function to better capture traffic dynamics such as fairness, congestion balancing, and efficient phase transitions. The model can also be upgraded to support predictive traffic behaviour, allowing agents to anticipate congestion patterns and adjust signal timings proactively. Integration with cloud-based platforms can enable centralized monitoring, performance analysis, and scalability for large deployments. These improvements will enhance the robustness, efficiency, and applicability of the system for future intelligent transportation solutions.

XIII. CONCLUSION

This project presented an intelligent traffic signal control system using Deep Reinforcement Learning to reduce congestion and waiting time at road intersections. The system utilizes both Single-Agent Deep Reinforcement Learning (SADRL) and Multi-Agent Deep Reinforcement Learning (MADRL) approaches, where agents learn optimal signal timings based on traffic conditions within the SUMO simulation environment.

The results demonstrate that the MADRL approach outperforms SADRL in managing multiple intersections, as it enables better coordination and adaptability across the traffic network. By dynamically adjusting signal phases based on vehicle count, queue length, and waiting time, the system significantly improves traffic flow and reduces delays.

Overall, the proposed approach provides an efficient, scalable, and adaptive solution for traffic signal optimization. It highlights the potential of reinforcement learning in intelligent transportation systems and offers a strong foundation for future development of smart traffic management solutions.

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APPENDIX

Training Cycle Algorithm Pseu- docode:

```
Initialize replay memory buffer D
Initialize Q-network with random weights θ
for episode = 1 to Max_Episodes do
  Reset SUMO environment and get initial state S_t
  while simulation time ≤ T do
  Select action A_t using ε-greedy policy
  Apply action A_t to traffic signal
  Execute simulation step in SUMO
  Observe next state S_t+1 and reward R_t
Store transition (S_t, A_t, R_t, S_t+1) in buffer D
  if buffer D has enough samples then
Sample mini-batch from D
Compute target Q-values using Bellman equation
Update network weights θ using backpropagation
end if
Update state S_t ← S_t+1
  end while
  Decay ε (exploration rate)
end for
```

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