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The Impact of Artificial Intelligence on System Response to Changing Traffic Signals

Sama Hassanin Hashim *

Collage Of Nursing, University of Babylon, Babylon, Hillah,51001, Iraq.

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Abstract

Urban traffic signal systems are facing increasing strain due to rising vehicle volumes, dynamic travel patterns, and unexpected disruptions. This paper investigates how artificial intelligence (AI) techniques especially deep reinforcement learning (DRL) and multi-agent/cooperative frameworks affect system responsiveness to changing traffic signals. We compare traditional signal control approaches (fixed-time, actuated, adaptive like SCOOT/SCATS) with AI-enhanced controllers, and propose an experimental framework using a microscopic traffic simulator (for example, SUMO) to assess performance under variable traffic demands. Metrics include average delay, queue length, throughput, and responsiveness to sudden changes (e.g., surge in traffic, incident). Results are expected to demonstrate significant improvements in responsiveness and efficiency while highlighting remaining challenges such as transferability, real-world deployment, and data requirements.

Keywords: Artificial Intelligence; Traffic system; DRL; Simulator

1. Introduction

Modern cities are increasingly confronted with complex traffic conditions, including variable flows, unexpected incidents, and increasing demand for mobility. Traditional traffic signal control systems—whether fixed-time, actuated, or early adaptive systems—are often limited by predefined rules, centralized decision making, and limited real-time adaptability. In response, AI methods, particularly reinforcement learning (RL) and deep RL, have emerged as promising techniques that can learn dynamic control policies from data and adjust signal timings in real time. This research aims to examine how AI changes the system's responsiveness to changing traffic signals, i.e., how quickly and effectively the system adapts to evolving traffic states, compared to conventional methods.

2. Literature Review

2.1. Conventional and Adaptive Signal Control Systems

Early and widely used systems such as SCOOT (Split Cycle Offset Optimisation Technique) and SCATS (Sydney Coordinated Adaptive Traffic System) adjust signal splits, offsets and cycle times based on sensor data and optimization rules. These have demonstrated improvements over fixed-time controls, but are still limited in handling highly dynamic, non-stationary traffic conditions.

2.2. AI-Based Methods in Traffic Signal Control

Recent years have seen a proliferation of AI-driven approaches:

- Surveys indicate that adaptive traffic signal control (ATSC) systems using fuzzy logic, metaheuristics, RL/DRL have shown significant promise in managing dynamic density flows.

* Corresponding author: Sama Hassanin Hashim

- In particular, deep reinforcement learning approaches have exhibited strong improvements: Gao et al. showed a DRL approach reduced vehicle delay by up to 47 % compared to longest-queue-first and up to 86 % compared to fixed-time control.
- More recently, work has focused on environmental metrics (e.g., CO_2 emissions) in AI-driven signal control. For example, one study achieved an 18 % reduction in CO_2 while maintaining performance through a DRL agent trained on queue length, speed and arrival rates.
- Multi-intersection and multi-agent RL frameworks face challenges of scale, coordination, non-stationarity, and transfer to real networks.

2.3. Key Gaps and Challenges

While the literature demonstrates strong potential, issues remain:

- Real-world deployment is still limited; many studies rely on simulation or small-scale setups.
- Scalability: controlling large networks of intersections with RL is non-trivial.
- Responsiveness: how quickly the system reacts to sudden changes (e.g., traffic surge, incident) is less studied.
- Interpretability, safety, robustness to changed conditions, generalization across cities and days remain open research topics.

2.4. Research Problem & Objectives

Problem Statement: Given dynamic traffic conditions with unforeseen changes (such as sudden surge in vehicle arrivals or lane blockage), how does employing AI-based signal control affect the system's responsiveness (i.e. , speed and effectiveness of adaptation) compared to traditional signal control methods?

Objectives:

- To quantify the improvement in responsiveness of an AI-based signal control system under variable traffic scenarios.
- To compare performance metrics (average delay, queue length, throughput, adaptation time) between conventional adaptive signal control and AI-based control.
- To identify practical challenges and limitations of AI-based approaches in signal control, particularly for real-world deployment in urban intersections.

3. Methodology

3.1. Simulation Environment

We propose using the SUMO traffic simulator to model one or more intersections. Traffic demand will vary over time, including baseline, surge (e.g., +50 % arrival rate), and incident scenarios (lane closure). Network geometry, lane configuration, and arrival patterns will be defined. The state space includes queue lengths, arrival rates, waiting times; action space includes signal phase selection, green time splits, cycle length adjustments.

3.2. Controllers

- Baseline: Fixed-time or actuated control (e.g., predetermined splits).
- Adaptive (traditional): A rule-based adaptive controller (e.g., mimicking SCOOT/SCATS logic).
- AI-based: A DRL agent (e.g., using DQN or PPO) trained to optimize a reward function combining delay minimization, queue minimization and adaptation speed.

3.3. Scenarios & Metrics

Scenarios:

- Normal flow
- Sudden surge
- Incident-induced disruption

Metrics:

- Average vehicle delay

- Average queue length per approach
- Throughput (vehicles per hour)
- Adaptation time: time taken for controller to restore traffic performance near baseline after disturbance
- Robustness: performance under sensor noise or demand variation

3.4. Experimental Procedure

- Train the DRL agent under a range of traffic demand profiles.
- Evaluate all controllers across each scenario for comparable periods (e.g., 2 hours simulation).
- Perform statistical analysis (e.g., ANOVA) to assess significance of differences.

4. Expected Results

We anticipate that the AI-based controller will outperform both fixed and traditional adaptive controllers in terms of lower delay and shorter queues, especially in disturbance scenarios (surge, incident). The adaptation time should be shorter with the DRL agent as it can learn to adjust phases more dynamically. We expect improvements in throughput and possibly reduced emissions (though emissions are not primary in this study). However, the AI approach may show variability, sensitivity to training conditions, and possibly degraded performance under unseen scenarios or highly noisy sensor data.

5. Discussion

The findings will be discussed in view of their practical implications. The improved responsiveness of AI-based control can support more resilient traffic systems in smart cities. Nonetheless, issues such as training data requirements, real-time deployment constraints, safety certification, generalization to new intersections, and integration with legacy infrastructure must be addressed. The discussion will also explore how multi-intersection networks and connected vehicle data could further enhance system responsiveness.

6. Conclusion

This research contributes by quantifying how AI techniques can improve system responsiveness of traffic signal control under changing conditions. While promising, further work is needed to scale to larger networks, integrate multi-agent coordination, ensure robustness, and operationalize in real urban settings.

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