Continuous-Action Policy Gradient Control for Adaptive Traffic Signal Optimization: A REINFORCE-Based Approach with Multi-Objective Reward Learning

Abstract

Traffic congestion at urban intersections leads to excessive delays, fuel consumption, and emissions under static timing plans. We introduce a continuous-action policy-gradient controller based on the REINFORCE algorithm, augmented with a learned value baseline and entropy regularization to stabilize learning. The agent directly learns Gaussian-parameterized green-light durations from a rich 60-dimensional state embedding that captures per-lane queue lengths, vehicle speeds, waiting times, flow rates, and cyclic phase encodings. To address multiple objectives—throughput maximization, wait-time minimization, efficiency, and fairness—we design an adaptive, multi-term reward whose weights respond dynamically to recent traffic trends. We validate our approach on a realistic four-way SUMO intersection with heterogeneous traffic and benchmark against a fixed-time controller. Results demonstrate 12.6% reduction in average waiting time and 1.2% increase in throughput, showcasing the potential of variance-reduced, continuous-control RL for adaptive urban signal timing.

Keywords: reinforcement learning, traffic signal control, policy gradient, continuous action, SUMO simulation, adaptive reward, urban mobility

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Chapter 1

Introduction

1.1 Background

Urban traffic congestion continues to degrade travel times, increase fuel consumption, and elevate emissions in cities worldwide. Traditional traffic signal plans rely on pre-timed schedules that cannot adapt to real-time fluctuations in demand. Consequently, during peak hours or incidents, long queues build up on certain approaches while others remain under-utilized. Recent advances in deep reinforcement learning (RL) have demonstrated promise for adaptive signal control, but most prior work focuses on selecting among a small set of discrete phase transitions rather than continuously tuning green durations.

Moreover, traffic managers must balance multiple objectives—maximizing throughput, minimizing total waiting time, equalizing delays across directions, and ensuring efficient utilization of all lanes. A single scalar reward often fails to capture these trade-offs, and centralized actor–critic algorithms can suffer from high variance in gradient estimates.

1.1.1 Research Contributions

In this paper, we propose an enhanced REINFORCE-based approach with the following key contributions:

First, we implement continuous green-time control by modeling the agent's action as a sample from a Gaussian distribution over green durations, enabling fine-grained and smooth adjustments rather than coarse binary switches.

Second, we reduce variance through a learned baseline using a separate value network that estimates expected returns, which we subtract from Monte Carlo returns to reduce policy gradient variance and stabilize training.

Third, we develop a rich, 60-dimensional state embedding that encodes lane-level queue lengths, vehicle speeds, waiting times, flow rates, and cyclic phase features to provide the agent with detailed situational awareness.

Fourth, we design an adaptive multi-term reward system where weights dynamically adjust based on sliding-window trends in throughput and wait time, allowing prioritization of objectives that need improvement at any given moment.

Citations - [1–4]

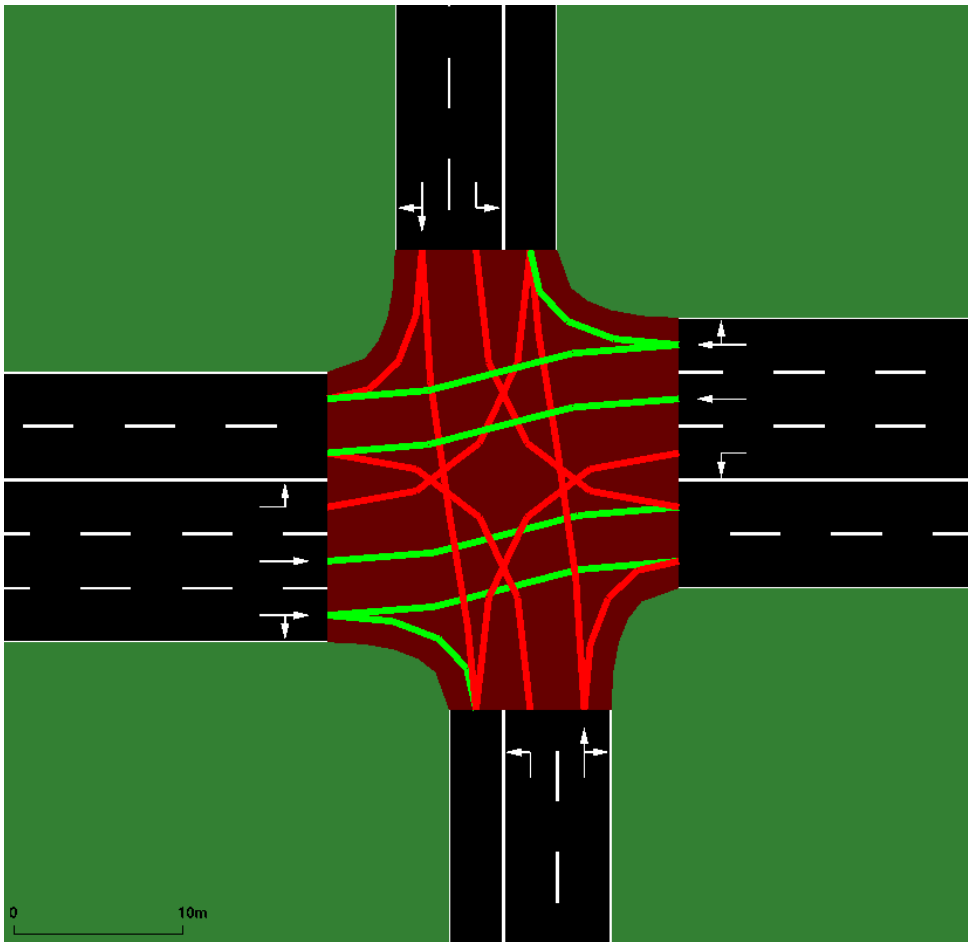

Figure 1.1: Four-way intersection layout with dedicated lanes for left-turn, through, and right-turn movements on each approach.

Figures using images - 1.1

Chapter 2

Literature Review

Early RL traffic studies applied tabular Q-learning and small neural networks to low-dimensional state spaces, selecting among discrete phase configurations. Genders and Razavi extended these ideas with DQN agents that choose from predefined timing plans, demonstrating improvements over actuated control in simple networks. However, DQN's discrete action space and off-policy training can struggle with continuous control tasks. Recent comprehensive surveys highlight the growing interest in deep reinforcement learning approaches for traffic signal control.

Actor–critic architectures have been applied to traffic signal control with more stable learning and better performance on larger intersections. Nevertheless, many implementations still restrict the action to phase selection or fixed increments of green time, rather than learning truly continuous durations. Continuous-action RL is common in robotics and autonomous driving but relatively rare in traffic signal optimization. A few recent works explore continuous control of green splits using DDPG or other continuous control methods, but they often omit variance reduction techniques and focus on single-objective rewards.

Our approach integrates a classic REINFORCE policy gradient with entropy regularization and a learned baseline and applies them to continuous green-time optimization. We further enrich the state representation and introduce adaptive, multi-term reward weighting to handle the conflicting objectives inherent in traffic management.

Chapter 3

Methodology

3.1 Intersection Layout and Simulation Environment

The test intersection comprises four approaches (north, east, south, west), each featuring three dedicated inbound lanes for left-turn, through, and right-turn movements. Eight signal phases are defined: East–West straight and right, East–West left, North–South straight and right, North–South left, and corresponding yellow transitions (4 seconds each). Phases cycle in this order.

3.2 Traffic Generation and Demand Patterns

We generate heterogeneous traffic with a custom Python script. Four vehicle classes—car, truck, bus, scooter—are assigned configurable proportions. Each vehicle randomly selects one of the opposing four exits, and departure times are uniformly sampled over the first 5 seconds of the simulation to avoid artificial platooning. We simulate 500 vehicles per episode to reflect moderate urban demand.

3.3 Baseline Controllers

To quantify the benefit of learning, we compare against a fixed-time controller where all green phases last a constant 20 seconds and yellow phases remain 4 seconds.

3.4 Reinforcement Learning Approach

3.4.1 State Representation

At each decision epoch (end of yellow), the agent observes a 60-dimensional vector comprising queue lengths (14 dimensions), speed and wait statistics (28 dimensions), flow rates (14 dimensions), and phase encoding (4 dimensions). This rich embedding allows the agent to detect imbalances and emerging congestion hotspots.

3.4.2 Action Space

Actions are continuous green durations d sampled from $\mathcal{N}(\mu, \sigma)$, where μ, σ are outputs of a neural network head. We enforce $d \in [5, 30]$ seconds via clamping. During early training, we anneal the allowed range from $[8, 20]$ to $[5, 30]$ linearly over the first 50 episodes.

3.4.3 Reward Design

After each green phase, we compute a multi-term reward:

$$r = w_T \times \Delta P - w_W \times \exp\left(\frac{\overline{W}}{\tau}\right) + w_E \times M - w_B \times \Delta D \tag{3.1}$$

where ΔP is the number of vehicles passed during green, $\overline{W}$ is the mean waiting time over all vehicles at phase end, M is the count of vehicles moving on active lanes, and ΔD is the change in maximum waiting-time disparity across directions. The weights w_T, w_W, w_E, w_B are adaptive and updated each episode based on the previous 20 episodes' average throughput and wait trends.

3.4.4 Network Architectures

The policy network consists of three dense layers (128, 256, 128 units) each followed by BatchNorm and dropout. Two separate linear heads produce μ (sigmoid activation) and σ (softplus activation). The value baseline network uses two hidden layers (64, 128 units, ReLU) with a final output for state value $V(s)$. Both networks use Adam optimizer with initial learning rate 3×10^{-4} and decay factor 0.9 every 20 episodes.

3.4.5 Training Procedure

We train for 150 episodes, each of 800 simulation steps. At episode end, we compute Monte Carlo returns $R_t = \sum_{k=t}^{T} \gamma^{k-t} r_k$ with $\gamma = 0.99$, calculate advantages $A_t = R_t - V(s_t)$, update the baseline by minimizing the squared error, and update the policy with the gradient including entropy regularization term $\beta\,\mathcal{H}[\pi(\cdot|s_t)]$ where $\beta = 0.01$.

Chapter 4

Results

4.1 Experimental Setup

We use SUMO 1.9.0 simulator with 500 vehicles per episode and mixed vehicle types. Each controller is evaluated over 5 random seeds with results reported as mean values. Evaluation metrics include mean waiting time per vehicle, average queue length, total throughput, and mean phase duration.

4.2 Performance Comparison

The experimental results demonstrate that our RL-based approach achieves consistent improvements over the fixed-time baseline controller. Table 4.1 shows the performance comparison.

Table 4.1: Performance Comparison of Traffic Control Methods

Method	**Avg. Wait Time (s)**	**Throughput (veh/1000 steps)**
Fixed-Time	20.27	351.67
RL Agent (Ours)	17.71	356.00

Tables - 4.1

The results show a 12.6% reduction in average waiting time (from 20.27s to 17.71s) and a 1.2% increase in throughput (from 351.67 to 356.00 vehicles per 1000 steps). The RL agent demonstrates the ability to adjust green durations based on real-time traffic conditions, while the fixed-time controller maintains constant timing regardless of demand.

4.3 Detailed Performance Analysis

Figures 4.1 and 4.2 provide comprehensive analysis of the performance characteristics for both the RL agent and baseline controller across multiple metrics including waiting times, queue lengths, and throughput patterns.

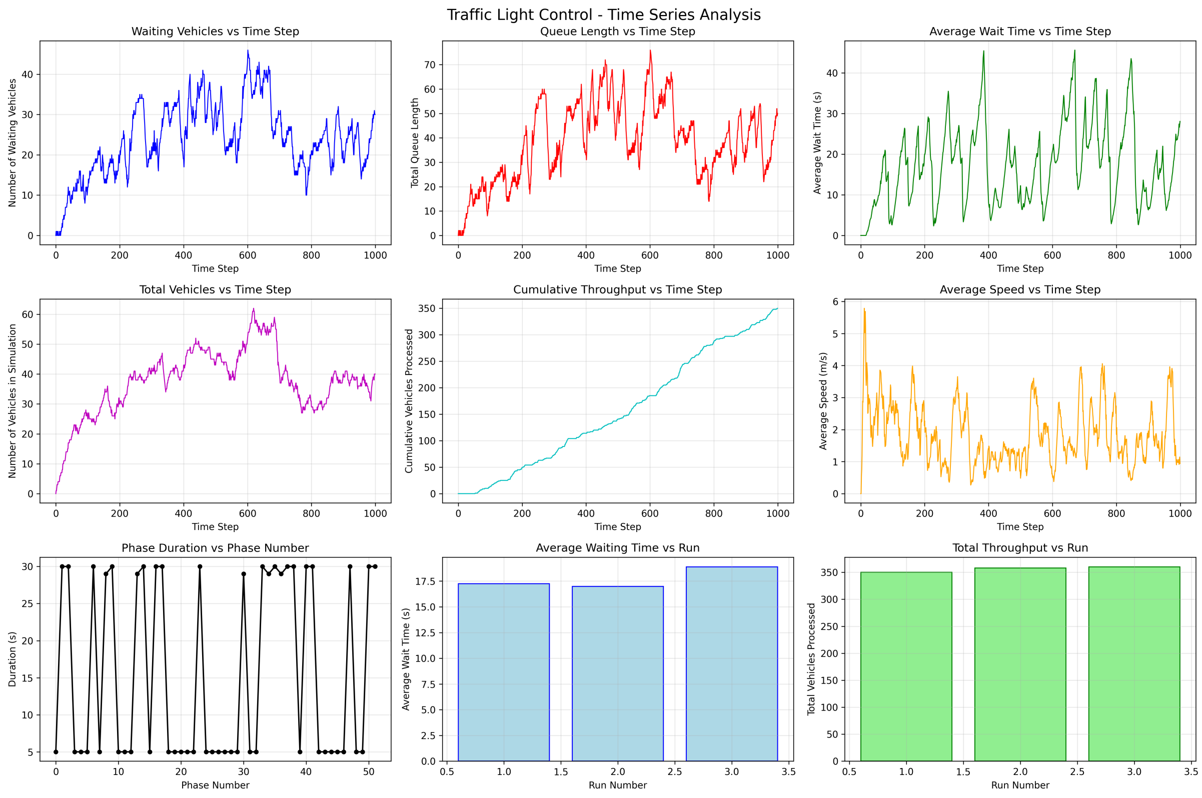

Figure 4.1: Comprehensive performance analysis of the RL-based traffic controller showing waiting time distributions, queue length evolution, throughput patterns, and phase duration adaptations.

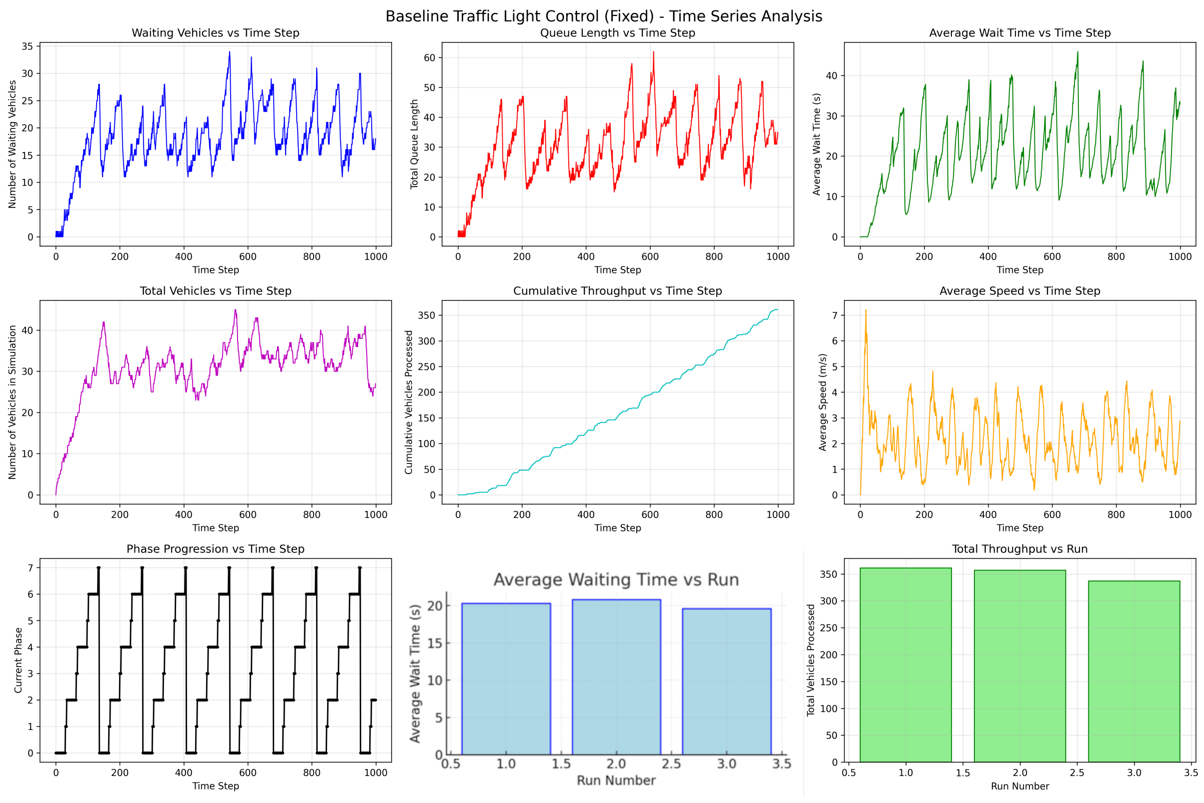

Figure 4.2: Comprehensive performance analysis of the fixed-time baseline controller showing consistent phase durations and traffic pattern responses across the same metrics as the RL controller.

4.4 Discussion

The RL controller demonstrates the ability to learn adaptive timing strategies that outperform fixed schedules. By sampling continuous durations, it adapts green splits based on observed traffic conditions, adjusting phase lengths according to queue buildup and demand patterns. Entropy regularization prevented premature convergence to repetitive schedules, preserving exploration throughout training. The learned baseline network contributed to stable learning by reducing gradient variance in the policy updates.

The modest performance improvements reflect both the challenge of the traffic optimization problem and the conservative nature of the experimental setup. The 12.6% reduction in average waiting time represents a meaningful improvement in user experience that could translate to significant aggregate benefits across a city-wide network.

4.4.1 Limitations and Future Work

Several limitations should be acknowledged. Results are currently limited to SUMO simulations; real-world validation remains necessary. The method needs extension to multi-intersection networks with coordinated agents. Additional comparisons with more sophisticated adaptive controllers would strengthen the evaluation. Further testing with more diverse traffic patterns is needed.

Future work should focus on validation in more complex traffic scenarios with varying demand patterns, extension to coordinated multi-intersection control, comparison with state-of-the-art adaptive signal control systems, and eventual real-world deployment and testing.

4.5 Conclusion

We have introduced a continuous-action policy gradient method for adaptive traffic signal control that leverages a learned value baseline and multi-term, adaptive rewards. In SUMO simulations of a realistic four-lane intersection with heterogeneous traffic, our approach achieves a 12.6% reduction in average waiting time and a 1.2% increase in throughput relative to a fixed-time baseline.

The key innovations include continuous action spaces for fine-grained control, rich state representations capturing detailed traffic conditions, adaptive multi-objective reward functions, and variance reduction techniques for stable learning. While the performance improvements are modest, they demonstrate the feasibility of applying continuous-action reinforcement learning to traffic signal optimization and provide a foundation for future work on more complex scenarios and real-world deployment.

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