# Implementation of An Urban Traffic Signal Control Based on Reinforcement Learning


## Master's Thesis of Alisena Nabizada

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### Introduction

Urban traffic congestion poses a significant economic and environmental challenge for cities worldwide, with intersections as a major bottleneck. Since the introduction of the first Traffic Signal Control (TSC) over a century ago, various control methods have been developed to safely and efficiently manage traffic flow at intersections. However, these systems rely heavily on simplified models that often fail to capture the dynamic complexity of real-world traffic conditions.

Recently, Reinforcement Learning (RL) based TSC has emerged as a promising alternative to current control methods, and various research studies have shown improvement in traffic conditions. However, most of these studies have been conducted in an idealized simulation environment, focusing only on private vehicles. On the other hand, the limitations of the currently implemented vehicle detection technology are not addressed. This study implements RL-based TSC by incorporating multimodal traffic and realistic limitations of currently available vehicle detection technology.

### Methodology

This study aimed to implement RL-based TSC under realistic traffic conditions and incorporate the limitations of the currently available vehicle detection technology. The RESCO toolkit and SUMO were used to implement the scenario. The RL agent operates at a real-world four-legged intersection in Ingolstadt, Germany, and observes multimodal traffic, including private vehicles, buses, and bikes, within a 70m video camera detection range. The state space includes the number of queued vehicles across different modes and the active signal phase. Every 10 seconds, the RL agent chooses a signal phase consisting of a set of non-conflicting phases. The reward function penalizes vehicle queues, with added weight for buses, and encourages phase stability.

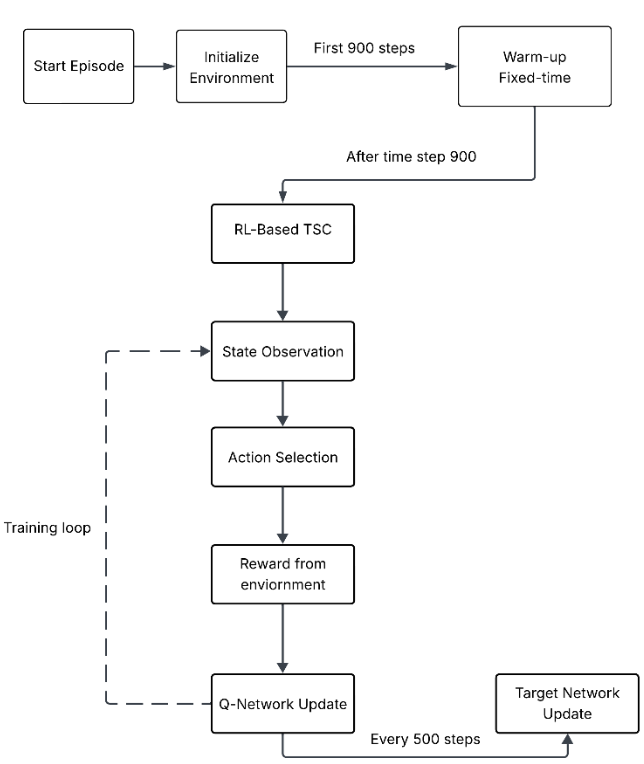


**Figure 1:** RL-based TSC training using Deep Q-Network

The model is trained using a Deep Q-Network algorithm with randomized peak-hour traffic and evaluated against fixed-time and actuated controls using real-world demand data.

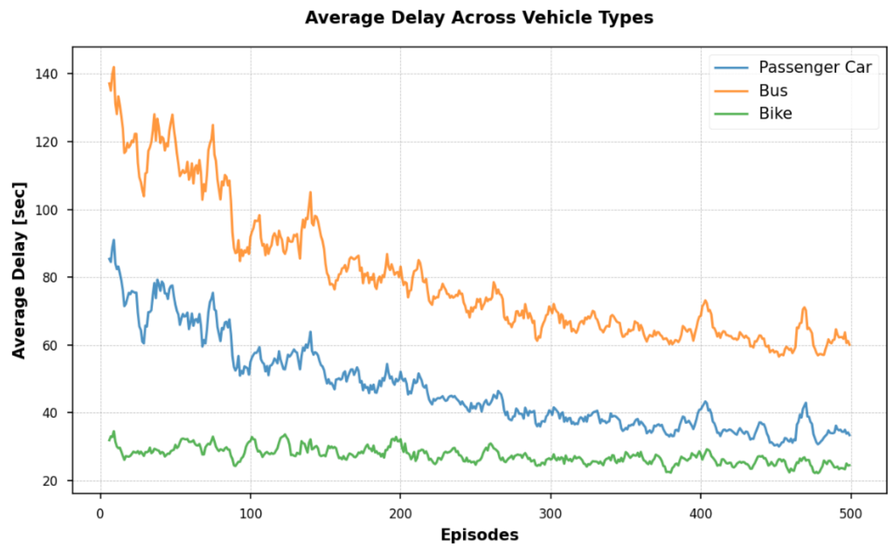


**Figure 2:** Average delay improvements across training episodes

### Results

The implemented RL-based TSC system demonstrated significant performance improvements over fixed-time and outperformed actuated TSC. It effectively reduces average delay and waiting time for all traffic modes. The results showed that the RL-based TSC agent can learn traffic patterns through a simple state space and reward function despite limited perception from a 70 m detection range.

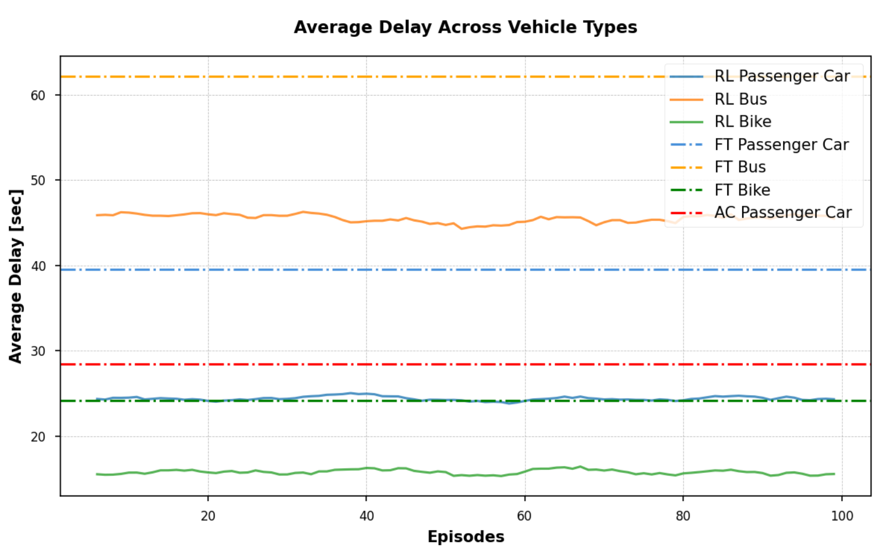


**Figure 3:** Benchmarking RL agent performance against fixed-time and actuated control for different vehicle types

### Limitations and Future Work

This study assumes perfect vehicle detection within a 70m range, which may not reflect real-world sensor errors. Intergreen times were simplified to a fixed 3 seconds across all movements. Future work may address these limitations and extend the approach to a corridor or network level setting.