Traffic Tune POC Presentation

Demonstrating AI-driven Traffic Signal Control

Team: Daniel Margolin, Tal Mekler, Eviatar Didon, Matan Drabkin

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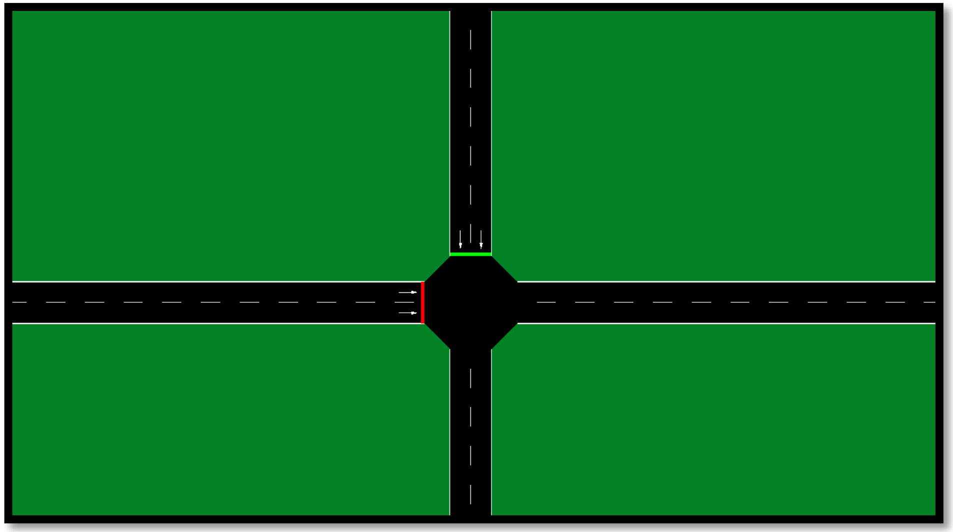
POC Overview

- Objectives:
  - Demonstrate the efficacy of an AI-driven traffic agent
  - Optimize traffic flow and reduce vehicle waiting times
- Approach:
  - Comparative demonstration at a single intersection
  - Fixed Time Policy vs. AI-driven Policy



Scenario Description

- Fixed Time Policy:
  - GGrr: Lane A green, Lane B red (42s)
  - yyrr: Lane A yellow, Lane B red (2s)
  - rrGG: Lane A red, Lane B green (42s)
  - rryy: Lane A red, Lane B yellow (2s)
  - According to SCOOT and SCATS policies (default for 2 lanes)
  - The convention is defined by the simulator
- AI-driven Policy:
  - Agent makes real-time decisions
  - Adaptable to traffic conditions

- The simulation includes about 2500-2600 vehicles in average and running for 1 hour
- Waiting Time is pre-defined to be 0.1 meters per second (threshold)

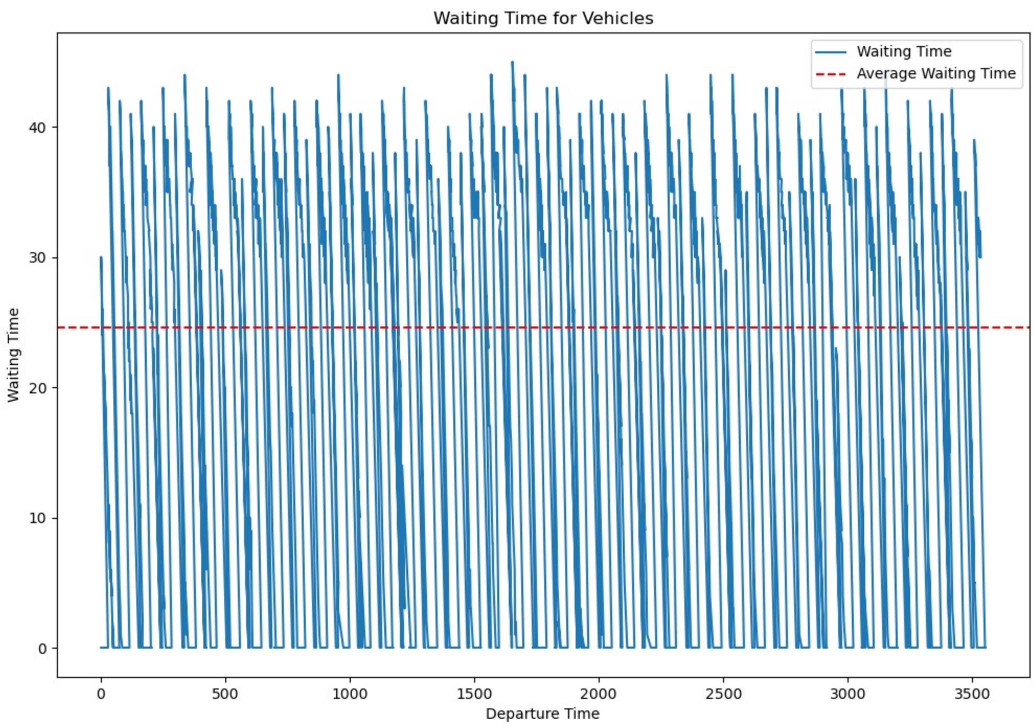
SUMO Environment Setup

- Environment:
  - SUMO (Simulation of Urban Mobility)
  - Configured for both Fixed Time and AI-driven policies
- Tools:
  - Jupyter Notebook
  - TraCI (Traffic Control Interface)
  - Gymnasium
  - SUMO-RL kit (Gym Wrapper)

Notebook preview

Performance Metrics

- Fixed Time Policy Results:
  - Mean Waiting Time: 24.59 seconds

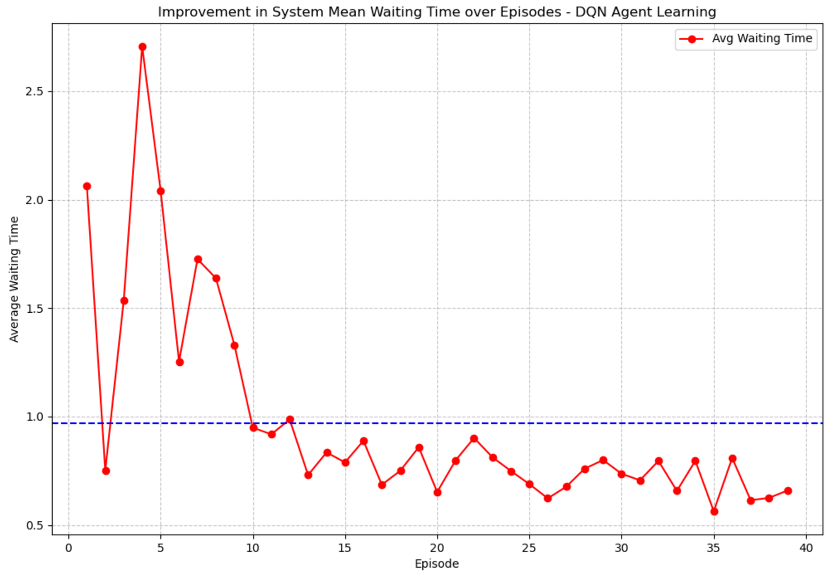


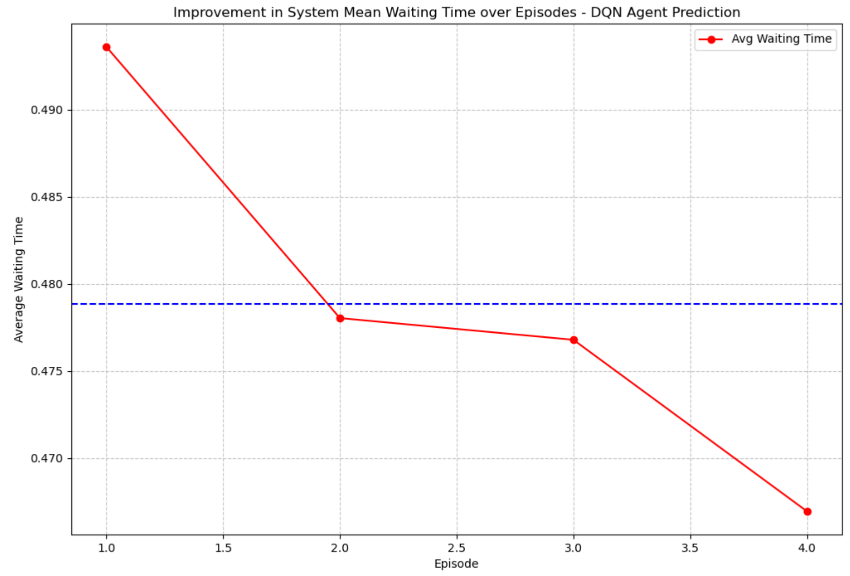
Fixed Time Policy

Performance Metrics

- Fixed Time Policy Results:
  - Mean Waiting Time: 24.59 seconds
- AI-driven Policy Results:
  - Mean Waiting Time: 0.48 seconds

24x improvement



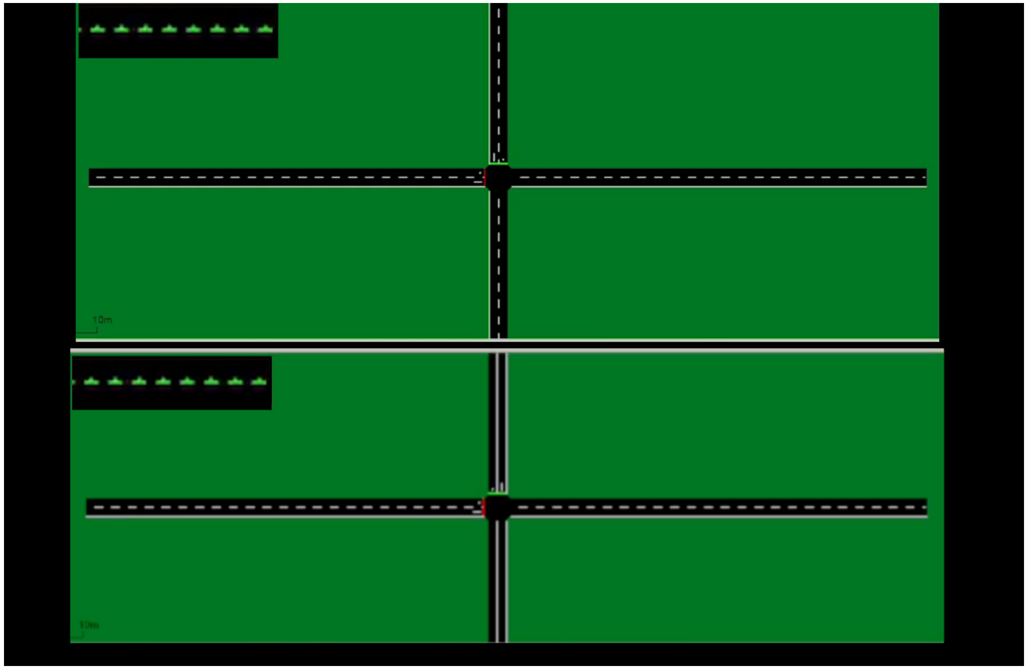


AI-driven Policy

Reward Improvement

Video Demonstration

- For illustration only



Conclusion

- Success Criteria Met:
  - Reduced average waiting time
  - Improved traffic flow
  - Positive feedback on adaptability
- Future Work:
  - Expanding the agent to more complex intersections
  - Expanding to multi agent approach
  - Experiments with different RL algorithms and various parameters changes