Congestion Estimation at Junction Using Reinforcement Learning

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Abstract - Traffic jam in city intersections is a big problem because of growing vehicle numbers and static traffic control systems limitations. Usual fixed-time traffic lights can't match changing traffic conditions, causing problems such as longer wait times, unequal flow of cars and pollution of the environment. To solve these issues, this project studies how to use State-Action-Reward-State-Action algorithm - a type of learning method that encourages improvements over time - for making optimization in controlling traffic lights more flexible and adjustable.

This project puts in place a system based on State-Action-Reward-State-Action in an imitation environment using Python's Pygame library. This is to replicate a four-way intersection. Important aspects being researched include the learning rate, discount factor and exploration rate that control how adaptable and performing the algorithm can be. The function of this system involves adjusting timings for traffic lights according to real- time patterns of congestion with the goal of reducing queue sizes as well as delay time for vehicles on average. Metrics like total throughput, waiting times of vehicles, and lengths of queues are monitored for assessing system effectiveness to guarantee productive learning and adaptability

Key Words: Traffic jam, City Intersection , Vehicle Number, congestion, Delay Time, Pollution.

1.INTRODUCTION

As urban populations grow and cities expand traffic congestion has become one of the most pressing issues faced by modern societies. Urban intersections or junctions are particularly vulnerable to congestion, as they represent critical points where multiple traffic streams intersect. With an ever-increasing number of vehicles, these junctions become choke points, leading to delays, fuel consumption, air pollution, and reduced quality of life. The problem is further aggravated during peak hours, emergency situations, or un- expected traffic events, where existing traffic signal systems struggle to cope.

Most current traffic management systems rely on fixed or pre-programmed schedules, which, while effective in controlled or predictable environments, struggle to adapt to dynamic and rapidly changing traffic conditions. This rigidity leads to several inefficiencies: vehicles often experience long waiting times at junctions due to the inability of signals to adjust to fluctuating traffic volumes, causing unnecessary idling even when there is little or no traffic in the other direction. Additionally, unbalanced traffic flow can occur, with one side of a junction becoming heavily congested while another remains underused.

2. METHODOLOGY

The methodology for this project involves designing and implementing a dynamic traffic light control system using the State-Action-Reward-State-Action (SARSA) reinforcement learning algorithm. The first step involves setting up a simulation environment using Python's Pygame library to replicate a realistic four-way traffic intersection. Vehicles are generated with random patterns to simulate real-world congestion, and traffic lights at each direction are programmed to have variable timing. The core of the system is the SARSA algorithm, which allows an intelligent agent to learn optimal light switching strategies through interaction with the environment.

The agent observes the current traffic state, takes an action such as switching the light phase, and receives a reward based on outcomes like reduced waiting time and improved traffic flow. This learning process is governed by key parameters including the learning rate, discount factor, and exploration rate, which are carefully tuned to enhance performance. A reward function is designed to encourage behaviors that minimize queue lengths and vehicle waiting times. The system is trained over multiple simulation episodes, and its effectiveness is measured using metrics such as average vehicle waiting time, total queue length, and traffic throughput.

3. SOFTWARE OVERVIEW

1. **Programming Language**: Developed using **Python** for its simplicity and flexibility in AI and simulation tasks.
2. **Simulation Library**: Utilizes **Pygame** to create a graphical simulation of a four-way traffic intersection, including roads, vehicles, and traffic lights.
3. **Core Algorithm**: Implements the **SARSA (State-Action-Reward-State-Action)** reinforcement learning algorithm to optimize traffic light control based on real-time traffic conditions.
4. **User Configuration**: Allows tuning of learning parameters and simulation speed for testing different scenarios.
5. **Extensibility**: Designed to be modular for easy updates or expansion to more complex intersections or real-world data integration.
6. **Reward System**: Custom reward function designed to reduce vehicle waiting time and queue lengths while increasing throughput.

4. SEQUENCE DIAGRAM AND ACTIVITY DIAGRAM

The sequence diagram illustrates the interaction between key components of the traffic light control system. Vehicles are first generated and added to the simulation environment, which tracks the current traffic state. This state is passed to the SARSA-based agent, which selects an action to control the traffic lights

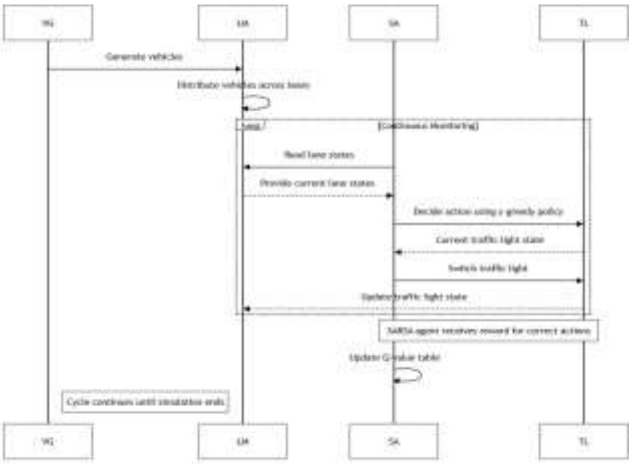

Fig 1. Sequence Diagram

STATE DIAGRAM

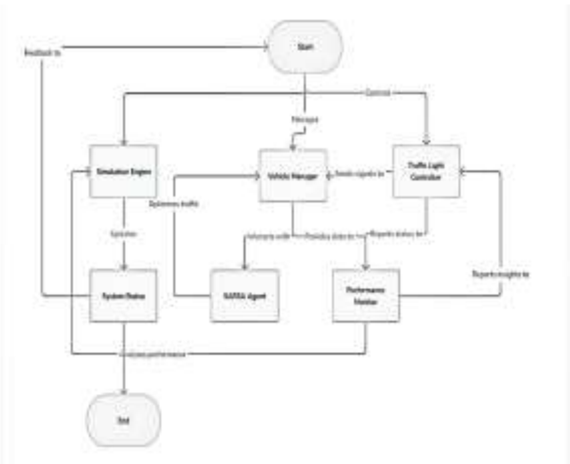

Fig 1.2 Activity diagram

5. RESULTS AND DISCUSSION

The results from the simulation show that the SARSA-based traffic light control system performs significantly better than traditional fixed-time signals. Over multiple training episodes, the agent was able to reduce average vehicle waiting time and queue lengths while increasing overall traffic throughput. The system demonstrated adaptability by adjusting signal timings based on real-time congestion patterns. As learning progressed, performance metrics stabilized, indicating effective convergence of the algorithm. These findings highlight the potential of reinforcement learning for improving urban traffic management through intelligent, data-driven control systems.

The agent also responded well to sudden traffic changes, showing strong adaptability to non-uniform flow. The reward function effectively guided the learning process, reinforcing decisions that minimized congestion. These outcomes demonstrate that a reinforcement learning approach, even in a simplified environment, can yield promising results for adaptive traffic control systems.

6. FUTURE WORK

Future enhancements for this project could include expanding the simulation to cover more complex traffic networks with multiple interconnected intersections, allowing the agent to coordinate traffic lights on a larger scale. Incorporating real-world traffic data and sensor inputs would improve the model's accuracy and practical applicability. Additionally, exploring other reinforcement learning algorithms, such as Deep Q-Networks (DQN) or Proximal Policy Optimization (PPO), could further improve learning efficiency and decision-making. Integrating pedestrian and public transport priorities, as well as emergency vehicle overrides, would make the system more comprehensive and realistic. Finally, developing a user-friendly interface for real-time monitoring and control would support easier deployment and analysis in urban traffic management systems.

The major contribution of this project lies in demonstrating the effective application of the SARSA reinforcement learning algorithm to optimize traffic light control at a four-way intersection. Unlike traditional fixed-time systems, the proposed approach adapts in real-time to changing traffic conditions, leading to reduced vehicle waiting times, shorter queues, and improved traffic flow. This work highlights how reinforcement learning can be practically implemented in a simulated environment using accessible tools like Python and Pygame, providing a foundation for more advanced smart traffic management systems. Additionally, the project explores the impact of key learning parameters on system performance, offering valuable insights for future research and development in adaptive traffic control.

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