Episodes-Based Traffic Signal Control: A Deep Reinforcement Learning Approach With Fluid-Dynamic Simulation

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Abstract. Traffic congestion remains a critical issue in urban traffic networks, leading to increased fuel usage, emissions, and frustration among commuters. This project suggests an AI- driven traffic optimization using the integration of Reinforcement Learning (RL) and fluid-based traffic flow simulation. Taking the Deep Q-Network (DQN) algorithm, the system trains an intelligent agent to learn dynamically adapting traffic light status towards minimizing road congestion. The road is modeled as a grid one-dimensional space in which the car flow is simulated by Taichi, an efficient computer library that simulates cars as a fluid to compute densities accurately. Initial traffic is imported from a density database, which represents car distribution on segments. For every time step, the agent observes significant features such as average, max, and min traffic densities, selects traffic light actions, and receives feedback according to the congestion status of the system. The simulation displays the instantaneous impact of changing lights, and the agent learns to avoid traffic congestion through continuous interaction. The final outcomes are visualized by heatmaps and animations to depict flow pattern improvement. This project describes how AI may control traffic systems autonomously and present a workable, scaleable solution for real-world city mobility problems.

Keywords: Traffic Congestion, Reinforcement Learning, Deep-Q Network, Fluid Based Simulation, Taichi

1 Introduction

Urban transport infrastructures across the globe face un- precedented pressure with the sudden rise in population density, vehicle possessions, and urbanization. As cities expand and traffic volume rises, traffic congestion has been one of the most severe issues confronting city planners and civic officials. Traffic congestion not only results in travel delay and lost productivity, but also has a very large impact on fuel consumed, the volume of greenhouse gas emissions, and commuter discontent overall. Conventional traffic regulation systems like fixed-timer traffic signals or basic sensor-based control strategies do not typically address the dynamism and complexity-based characteristics of modern urban traffic. These vintage systems are not flexible and cannot react to actual-time fluctuations in traffic volume, leading to undue occupation of road lanes and repetitive bottlenecks.

In modern times, the use of Artificial Intelligence (AI) and machine learning-based

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algorithms has been exhibiting immense potential in attempting to solve numerous issues in transport systems. Among them, Reinforcement Learning (RL) has proven to be a very powerful paradigm for constructing adaptive and self-optimal control policies. RL allows agents to learn the best action by interacting with their environment and getting feedback in the form of rewards. In traffic optimization, RL provides a robust and dynamic framework for learning traffic light control strategies that reduce congestion, improve travel times, and minimize environmental effects.

This paper proposes a new AI-driven method combining Reinforcement Learning with fluid-based simulation of traffic flow in the optimization of city traffic. In particular, we employ an agent that is trained as a Deep Q-Network (DQN) to manage traffic light states for the purpose of minimizing traffic congestion on a simulated sample road network. In contrast to rule-based agents, this type of agent decides its strategy by continuously trying out various traffic light settings and adapting to the result. The highway is represented as a one-dimensional grid, with each cell representing a part of the road with a given vehicle density. This configuration simplifies traffic behavior to a computationally efficient simulation that can be experimented with One interesting element of this project is the implementation of Taichi, a numerically high-performance computing library tailor-made for numerical simulations, when simulating traffic flow as fluid. Under the fluid-based setting, cars are simulated similar to particles in a fluid flow and their transition across segments regulated through low-flow rules. This method better mimics traffic patterns and facilitates analysis of trends in vehicle travel and density more easily. Traffic lights at these special grid locations are familiar to the model, and their color (red or green) regulates vehicles' motion within the simulation in a direct manner. The states of traffic lights are managed by the DQN agent and learn how to adjust them judiciously according to environmental feedback. Simulation is started using the system, which loads preliminary traffic information from the preprocessed database with densities of vehicles per grid segment.

During each time step, the agent experiences a state representation in the average, maximum, and minimum forms of traffic densities. It decides based on this input regarding a set of actions—i.e., the color (green or red) of each traffic light. The simulation then adjusts traffic flow accordingly and computes a reward based on general traffic condition. The reward function generally punishes high con- gestion rates in an attempt to motivate the agent to lower overall traffic density. Throughout many training episodes, the agent is trained to recognize traffic behavior patterns and assumes strategies that optimize flow efficiency. Performance of the trained agent is quantified by executing an optimized simulation and visualizing with heatmaps and animations. Visualization tools both present an intuitive indication of how traffic density changes with time and the extent to which the agent is able to mitigate congestion. High-density areas are depicted as hotspots, so stakeholders can visually identify exactly where and how traffic flow has been optimized using AI.

In summary, this project proves the possibility and efficacy of integrating Reinforcement Learning with fluid-based traffic simulation to achieve intelligent traffic light control.

It proves the ability of AI to learn autonomously how to navigate through a complex city environment and make real-time decisions that result in tangible transportation improvements. By making the outcomes transparent, it also completes the loop between technical implementation and true impact, and demonstrates a scalable solution for intelligent, data-driven city mobility.

2 Literature review

The application of Reinforcement Learning (RL) and Artificial Intelligence (AI) to traffic signal optimization has been an active area of research addressing the limitations of traditional traffic control systems. Early investigations, such as the work by [1], demonstrated the feasibility of applying Q- learning to adaptive control at individual intersections, laying the groundwork for dynamic traffic flow management.

The field progressed with the emergence of Deep Reinforcement Learning (DRL), introducing neural networks to approximate optimal policies. Researchers developed sophisticated approaches using Deep Q-Networks (DQN) to control multiple intersections, proving significantly more efficient than conventional fixed-time methods [2]. These RL systems were designed to fine-tune traffic light timings based on real- time environmental inputs, enabling more nuanced control of complex urban traffic networks.

Beyond single-agent approaches, Multi-Agent Reinforcement Learning (MARL) emerged as a promising solution for managing larger traffic systems. This paradigm treats each traffic light as an independent agent capable of localized actions while maintaining communication with other agents. Research by [3] demonstrated the potential of MARL agents to collaborate in mitigating congestion across coordinated intersections. However, these decentralized approaches face challenges, including non-stationarity and coordination difficulties, especially with a high number of agents. Concurrently, researchers explored fluid-based models for traffic simulation, applying fluid dynamics principles to vehicle traffic. The Lighthill-Whitham-Richards (LWR) model from the 1950s provided a theoretical foundation by modeling traffic density as a continuous variable subject to conservation laws [4]. Recent computational platforms like Taichi have enabled rapid real-time simulation of these models, prov- ing particularly advantageous in scenarios requiring quick computation and less computationally expensive approaches compared to agent-based microsimulation.

An innovative research direction has focused on integrating learning-based control with simulation platforms. Hybrid models have been developed that incorporate traffic simulation with reinforcement learning, allowing agents to learn from simulated traffic scenarios [5]. These systems facilitate RL agents' interaction with realistic environments, accelerating the training process and enabling the development of more efficient traffic control policies.

Visualization has emerged as a critical component in traffic optimization research. Researchers have emphasized the importance of heatmaps, density plots, and animations in interpreting and analyzing traffic flow behavior [6]. These tools prove essential in identifying congestion points, understanding traffic light change effects, and evaluating the efficacy of optimization interventions.

The theoretical advancements have begun to translate into practical applications in smart city environments. Notable deployments, such as the Surtrac system in Pittsburgh, have demonstrated real-world implementations of AI-driven adaptive traffic signal control [7]. These initiatives have shown measurable improvements in delay reduction and emission control, validating the potential of intelligent traffic management systems.

While existing literature provides robust support for applying reinforcement learning to adaptive traffic light management and validates fluid-based modeling as a valuable simulation approach, few research efforts have successfully integrated these methodologies into a comprehensive framework. The present project aims to bridge this critical gap by combining a Deep Q-Learning agent with a fluid-dynamics-based simulation engine, promising an intelligent and computationally efficient traffic control system.

More recent research has explored advanced machine learning techniques beyond traditional Reinforcement Learning approaches. [8] introduced a novel framework utilizing federated learning for distributed traffic signal control, addressing previous limitations in centralized decision-making. This approach allows for more robust and privacy-preserving optimization across different urban intersections.

The integration of emerging technologies has further expanded traffic management capabilities. [9] demonstrated the potential of sensor fusion techniques, combining data from multiple sources including GPS, LIDAR, and IoT devices to create more comprehensive traffic prediction models. These multi-modal approaches significantly improve the accuracy of traffic flow forecasting and signal optimization.

Deep learning architectures have shown promising results in complex traffic management scenarios. [10] proposed a hybrid neural network model that combines convolutional and recurrent neural networks to predict traffic flow with unprecedented accuracy. The model effectively captures both spatial and temporal dependencies in urban traffic patterns.

Environmental considerations have become increasingly important in traffic optimization research. [11] explored the intersection of traffic management and emission reduction, developing algorithms that not only minimize congestion but also prioritize reducing carbon emissions. This approach demonstrates the potential for AI to address both traffic efficiency and environmental sustainability.

Edge computing and 5G technologies have opened new avenues for real-time traffic management. [12] introduced a framework for low-latency traffic signal control using edge computing architectures, enabling near-instantaneous decision- making and reducing computational overhead associated with traditional centralized systems.

The challenges of transfer learning in traffic optimization have been addressed by recent studies. [13] proposed innovative approaches to adapt traffic control policies across different urban environments, overcoming the traditional limitations of context-specific training models. This research suggests the potential for more generalizable traffic management strategies. Emerging research has also focused on the resilience of AI-driven traffic systems. [14] investigated the robustness of machine learning models under various urban scenarios, including unexpected traffic disruptions and adverse environ- mental conditions. Their work provides critical insights into developing more adaptable and reliable traffic optimization systems.

3 Methodology

3.1 Data source

The dataset utilized in this research originates from the United States Department of Transportation (USDOT) [15], specifically drawn from high-resolution traffic trajectory data. The dataset captures detailed vehicular movement characteristics across multiple urban transportation corridors, including highways such as US-101 and I-80.

The raw data encompasses a comprehensive set of attributes critical for traffic flow analysis:

- **Spatial Attributes:** Local and global coordinates (Local_X, Local_Y, Global_X, Global_Y)

- **Vehicle Characteristics:** Vehicle length, width, class,

velocity, and acceleration

- **Temporal Metadata:** Global time, frame identification, total frames

- **Traffic Context:** Lane ID, section ID, direction, movement

- **Interaction Metrics:** Space headway, time headway, preceding and following vehicle information

The original dataset was collected using advanced tracking technologies, providing a granular view of vehicular dynamics in complex urban traffic environments [16].

3.1.1 Data Cleaning and preprocessing

The raw trajectory data underwent a rigorous preprocessing pipeline to prepare it for reinforcement learning-based traffic optimization:

Initial data transformation involved converting the high- dimensional raw data into a more compact representation:

- Reduced dimensionality from 30+ features to key state representation features

- Converted continuous spatial coordinates to normalized grid-based representations

- Standardized vehicle characteristics to enable consistent agent observation

Several critical cleaning steps were implemented:

- Removal of duplicate entries and redundant records

- Handling of missing values (noted as 'NA' in the original dataset)

- Outlier detection and treatment using statistical methods
- Normalization of numerical features to ensure consistent scaling

Advanced feature engineering techniques were applied to extract meaningful representations:

- Derived features such as relative velocity, acceleration profiles
- Computed aggregate metrics for traffic density estimation
- Created state representation vectors suitable for reinforcement learning input

Specific preprocessing steps were tailored for the Deep Q- Network (DQN) agent:

- Discretization of continuous state spaces
- Creation of episode-based data structures
- Generation of reward signals based on traffic flow characteristics
- Preparation of state transition matrices for agent learning

The preprocessing pipeline ensures that the raw trajectory data are transformed into a format optimally suited for our fluid-dynamics-based reinforcement learning approach to traffic signal optimization.

3.2 Overview of Taichi

Taichi is an open-source, high-performance programming language specifically designed for numerical computation and real-time physical simulation. It is developed to bridge the gap between usability and computation efficiency. Taichi enables programmers to write high-level Python-like code that can be compiled into low-level optimized machine instructions. Taichi supports multiple backend architectures like CPUs, NVIDIA GPUs with CUDA, and Apple's Metal on macOS and hence is portable on leading platforms.

Taichi excels at use cases that require fine-grained par- allelism, dynamic memory management, and rapid iterative updates—such as particle simulations, fluid dynamics, and in this project, traffic flow simulation. One of its standout features is a just-in-time (JIT) compilation system that com- piles Python-like kernels into rapid native code, allowing real-time simulation performance with maintained developer productivity.

Taichi is employed in this project to simulate traffic flow along a 1D grid of roads by simulating vehicle density as a continuous fluid field. Flow rates at specific grid points are influenced by traffic signals, and the simulation's real-time updates these fields in accordance with the action performed by the agent. This model tremendously minimizes computation at the vehicle level and supports rapid iterations, which are the most critical aspect in reinforcement learning environments.

Architecture of Taichi: Taichi architecture is built in the trade-off between high-level programmability and low- level execution performance. The foundation of Taichi is a Python frontend where computational kernel programming is performed using decorators such as @ti. kernel. The kernels are compiled to intermediate representation (IR) and subjected to various compiler optimizations such as constant folding, loop unrolling, and memory coalescing. The IR is then compiled to backend-specific machine code, for example, CPUs (via LLVM), NVIDIA GPUs (via CUDA), and the Metal API on Apple. Memory management, field allocation, and kernel scheduling are handled across devices by a shared runtime system. It handles dynamic data structures as well as features like automatic differentiation. Taichi is based on a data- oriented programming model under which it is able to provide high-performance real-time simulations due to the capability of developers to explicitly define multi-dimensional fields and data layouts. This renders Taichi particularly well-suited for use in applications involving fast, iterative computation such as fluid dynamics, physics simulation, and traffic flow optimization. Fig. 1 shows the Architecture of Taichi.

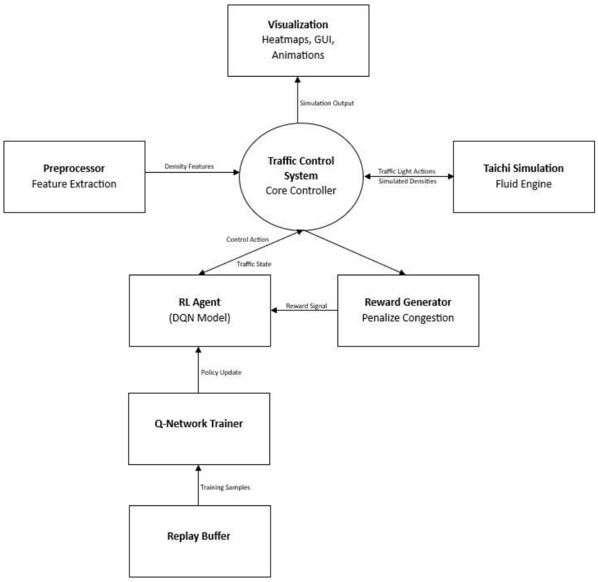

Fig. 1. Architecture of Taichi.

3.3 Model Training

The training phase of the reinforcement learning model within this project involves the learning of an agent to learn to optimize traffic light control through real-time feedback from a simulated environment. The agent used is a Deep Q- Network (DQN), which combines Q-learning and deep neural networks to estimate the optimal action-value function. The model has an input state of three most important features: average traffic density, max density, and min density for each road segment. These are brief but informative descriptions of the traffic condition at every time step.

The DQN agent selects actions by controlling the states (green or red) of a predetermined number of traffic lights at predetermined grid positions. In training, it experiments with various light state combinations in an ϵ-greedy manner, balancing exploration and exploitation against one another. Exploration rate ϵ begins at 1.0 and diminishes over time to a minimum level, so the agent shifts from random action to learned, deterministic policy as training progresses. Actions are evaluated against a reward function that is intended to punish higher overall vehicle density, thereby inducing the agent to learn traffic light patterns that alleviate congestion.

Training proceeds over thousands of episodes, with each episode being a complete run of the traffic simulation from a starting point. The agent takes an action on the environment in every time step, observing the outcome of its action and experiencing tuples of the type ⟨state, action, reward, next_state⟩. Experiences are stored in a replay buffer and sampled in mini-batches for updates of stochastic gradient descent. This type of approach reduces correlation between successive experiences and improves training stability. The Q-network is learnt by minimizing the mean squared error between target Q-values and estimated Q-values, the latter obtained through computation from the Bellman equation.

The environment itself is simulated with a fluid-based traffic model coded in Taichi, allowing for efficient computation of vehicle flow across grid segments. The effect of each action can be seen in the simulation instantly, and the agent perceives these changes as differences to traffic density distributions. Each step of the environment is the vehicle flow according to the current light configuration, and this density field that has been formed through it is utilized to compute the reward as well as the next state.

The convergence of training is monitored in terms of the agent’s total amount of reward gained across episodes. As training progresses, the agent learns more and more effectively to reduce traffic congestion, as indicated in progressively less negative reward values. At the end of the training, the optimal policy is verified by running the simulation with the learned light control policy. Evolution of traffic density throughout the test runs is observed as heatmaps and animations that offer an instant, intuitive insight into how learned model alleviates congestion over time.

3.4 Visualization

Traffic flow visualization plays a critical role in understanding complex traffic dynamics and validating the performance of the reinforcement learning model. In this section, we present a series of visualizations that demonstrate the evolution of traffic patterns under our control strategy.

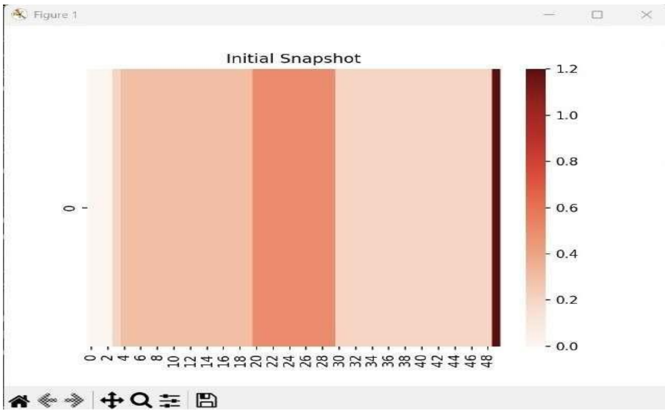

Fig. 2. Initial traffic state showing heterogeneous density distribution across road segments. The heatmap reveals three distinct zones of varying congestion levels (0.3, 0.5, and 0.2), consistent with the initialization parameters defined in the simulation code.

Fig. 2 presents the initial state of our traffic simulation with a non-uniform density distribution. The visualization employs a color gradient where deeper colors indicate higher traffic density. This initial heterogeneous distribution is particularly important for testing our reinforcement learning model under realistic conditions, as real-world traffic rarely exhibits uni- form congestion patterns.

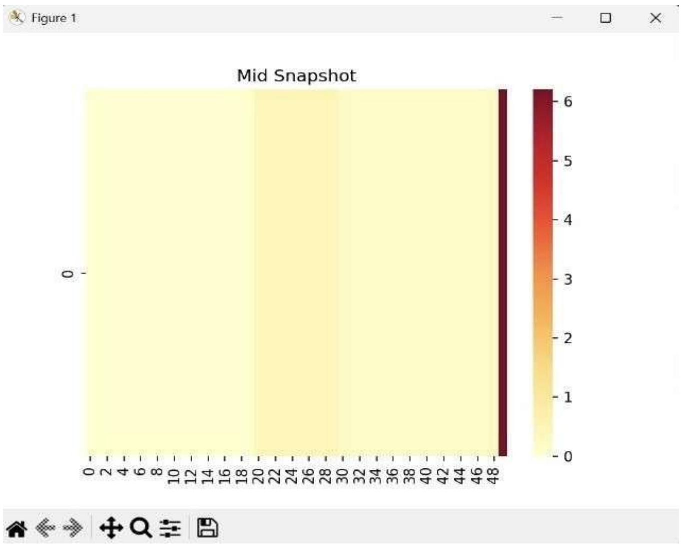

Fig. 3. Mid-simulation traffic state demonstrating density redistribution. At this intermediate point, we observe how traffic has begun to propagate through the network, with density patterns shifting compared to the initial state.

As the simulation progresses, Fig. 3 captures an intermediate state where traffic density has begun to redistribute. This mid-simulation snapshot is crucial for understanding the dynamic behavior of our traffic model. We can observe that the initially distinct zones have started to blur as vehicles move through the network. The adaptive traffic signal control implemented by our reinforcement learning agent has begun to influence traffic flow, prioritizing high-density segments to reduce overall congestion.

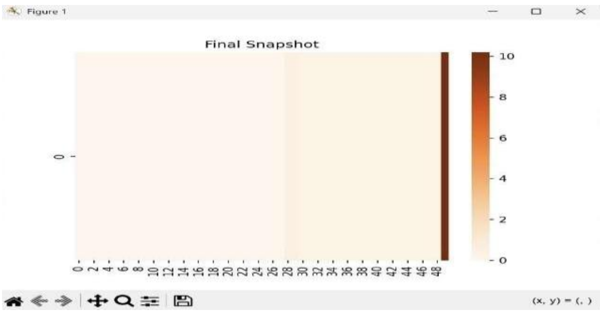

Fig. 4. Final traffic state after complete simulation showing the outcome of traffic flow management. The heatmap demonstrates significant congestion reduction across most road segments, with remaining density concentrated primarily at the rightmost edge.

Fig. 4 displays the final state of the traffic network after the simulation has completed. The most striking observation is the significant reduction in congestion across the majority of road segments, as evidenced by the predominantly light coloration. However, a notable concentration of traffic remains at the rightmost edge of the simulation space, which is consistent with our traffic flow model where density can accumulate at network boundaries when outflow is restricted.

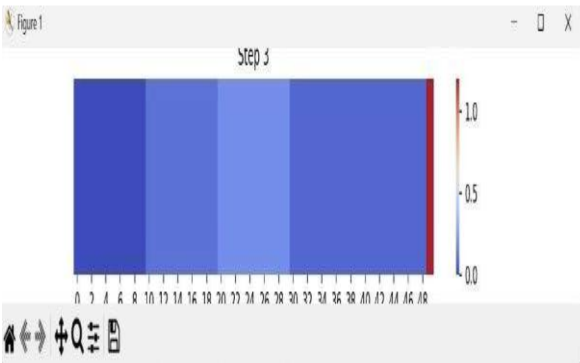

Fig. 5. Traffic density at simulation step 3, showing predominantly low congestion (blue) with a high-density region (red) forming at the rightmost edge of the simulation space.

To better understand early traffic dynamics, Fig. 5 presents the system state at step 3, revealing how traffic propagates during early simulation stages. The traffic density remains low (blue) throughout most segments, with congestion (red) beginning to form at the rightmost segment. This pattern is consistent with the simulation model's update logic, which transfers density from one segment to the next when traffic lights permit flow.

Interactive Visualization: Beyond static heatmaps, we implemented interactive visualization tools to provide dynamic views of the simulation. These tools allow for real-time monitoring and analysis of traffic conditions.

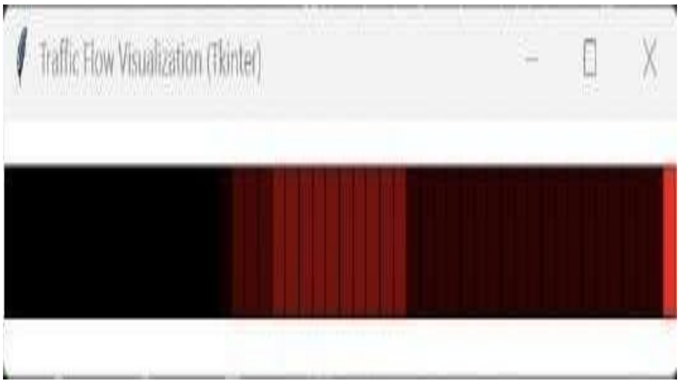

Fig. 6. Simple Tkinter-based visualization of traffic flow, where red intensity indicates congestion level. This alternative visualization method provides a compact representation for rapid assessment.

Fig. 6 shows a simplified Tkinter-based visualization that uses color intensity to represent traffic density. This compact representation enables quick assessment of system-wide congestion levels during simulation, providing immediate feedback on the effectiveness of control strategies.

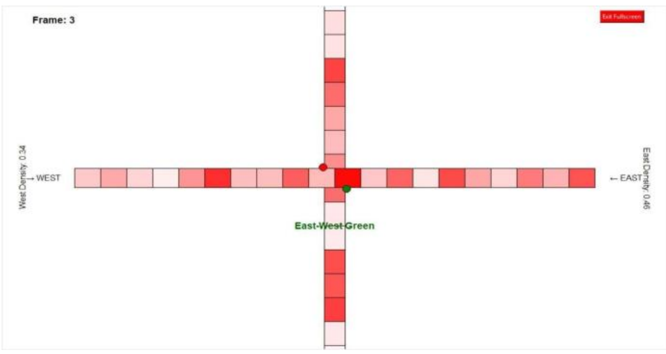

Fig. 7. Four-way intersection visualization with traffic light control showing North-South and East-West roads with varying traffic densities (red intensity) and current traffic light states.

The most comprehensive visualization is presented in Fig. 7, which depicts a four-way intersection with real-time traffic signals. This visualization integrates directional traffic representation, density indicators through color intensity, current traffic light states, and density statistics for each direction. In this fig, the East-West direction has been assigned a green light, while the North-South direction has a red light. This decision aligns with the observed density patterns, as the East- West corridor (0.46 average density) requires priority over the North-South corridor (0.34 average density).

Visualization Implementation Details: Our visualisation pipeline employed multiple libraries and approaches, including Matplotlib and Seaborn for static heatmaps, animation capabilities using FuncAnimation, Tkinter for interactive GUI development, and Streamlit for web-based accessibility. This diversity of visualization approaches enables both detailed scientific analysis and intuitive presentation of results to non-technical stakeholders. Through these visualizations, we can observe how our reinforcement learning algorithm detects congestion patterns and adjusts traffic signals accordingly. This visual evidence corroborates the quantitative performance reported in the following section.

4 Results and Discussion

4.1 Model performance metrics

The Deep Q-Network (DQN) agent showed measurable improvement in learning across successive training episodes. As the model trained, the overall reward per episode showed consistent improvement, indicating that the agent was learning to reduce traffic congestion through traffic light control optimization. The performance measure used was the overall reward, which was the negative sum of traffic density across all road segments per time step. A higher (less penalizing) cumulative reward was linked to smoother traffic movement and less congestion. In early episodes, the agent typically earned penalties that neared the theoretical ideal due to poor timing in light switching. In final episodes, the agent always generated better rewards, meaning smoother traffic switching and improved choice.

4.2 Simulation Scenario Outcomes

The simulation was run under an east-west and north-south controlled crossroad-like urban setup. The grid of traffic was visualized real-time with the help of a GUI interface and also post-processed in heatmaps and snapshots of density. Initially, dense red patches appeared, which indicated congestion near junctions. With time, as the agent optimized light control policies, the heatmaps transformed from heavy red to lighter color, which indicated more uniform vehicle spread and greater throughput.

Snapshots labeled" Initial"," Mid", and" Final" clearly showed how traffic concentration was rearranged. The initial snapshot represented dense congestion at center junctions. The mid snapshot represented some relief, while the final snapshot indicated the general smoother flow with fewer congestions bunching up—verifying the effectiveness of agent learning.

4.3 Computational Efficiency

The simulation model was done with Taichi, which was extremely effective in real-time vehicle flow numerical simulation along a grid-based road model. Parallelism and GPU-friendly Taichi backend allowed the environment to react extremely fast to agent actions and update the state in milliseconds per time step. Fluid-based simulation, in contrast to vehicle-level microsimulation, significantly reduced the computation cost. This permitted multiple episodes of training to be conducted and policy assessment with little latency, making the framework eligible for real-time or near-real-time deployment.

4.4 Interpretation of Key Findings

The visualizations and performance measures collectively confirm that the proposed RL-based system can actually learn and adapt to traffic conditions. The agent was capable of generating policies that balanced green light allocations across crossing roads, prevented queue building, and smoothed traffic flow transitions. The heatmap plots and GUI interface emphasized the spatial impact of light decisions—spaces downstream of green lights experienced faster flow and lower density, showing the model's ability to decrease congestion locally and network-wide.

Also, the reward curve during training showed convergence to an optimal policy. A comparison between fixed-timer defaults vs. agent-controlled revealed AI-based control with fewer deadlocks and improved sharing of vehicle flow across space and time.

4.5 Limitations and Constraints

Although promising results were obtained, the project had several limitations. Firstly, the network of roads was modeled as a one-dimensional simplified grid with constant inflow rates. Real networks are multi-lane, comprised of heterogeneous vehicle dynamics, and feature pedestrian crossings and emergency vehicles, which were not modeled here. Second, the Taichi reward function was based solely on density minimization without accounting for problems like delay, fuel consumption, or environmental factors. In addition, the agent was trained in a fixed environment and not tested under varying inflow conditions, which could limit generalizability. Thirdly, while Taichi allowed for fast simulations, integration with large-scale, multi-agent RL systems can be problematic due to scalability issues owing to limitations in GPU memory.

4.6 Future Research Directions

Potential future extensions are to model multi-lane inter- sections, adaptive inflow, and heterogenous vehicle classes. Incorporating real traffic data streams into the environment or incorporating public traffic datasets like NGSIM would add real-world validity. The agent architecture can also be improved with the use of more advanced RL algorithms like Proximal Policy Optimization (PPO) or Soft Actor-Critic (SAC) for better stability and convergence.

As for system deployment, the simulation platform may be extended to support integration of IoT sensor data to enable real-time AI-based signal control in smart city use cases. The integration of multi-objective rewards— congestion, emissions, and fuel burn—would also give a more robust optimization setting. Including multi-agent reinforcement learning (MARL) to coordinate multiple intersections at once would further allow scalability and responsiveness for massive-scale traffic systems.

5 Conclusion

This work proposes a novel paradigm for smart urban traffic management using Deep Reinforcement Learning (DRL) and fluid-based traffic simulation for real-time signal control optimization. The traffic here is represented as a continuous flow and a Deep Q-Network (DQN) agent is utilized, where the system can learn to decongest efficiently by controlling traffic lights in a smart way. The use of Taichi for simulation enabled effective, high-speed simulation of traffic flows along grid segments with an interactive and responsive training and testing environment for agents.

The learning agent recorded a visible traffic pattern and improvement of flow observed via various heatmaps and reward plots. Visualization outcomes of simulation example snaps such as starting frame snaps, middle snaps, and ending frame snaps confirmed the efficiency of the agent to re- move congestion points and dynamically manage traffic. GUI visualizations in real-time provided an easy comprehension of automobile density patterns and control logic activation, rendering the system readable and comprehensible.

Despite its good performance, the model lacks functionality such as multi-lane simulation, dynamic inflow patterns, or real-world features like emergency vehicle and pedestrian interaction. However, the framework is a decent proof of concept, illustrating the practical viability of combining RL with light traffic modeling methods.

More effort will go into scaling the system up into multi- intersection environments, leveraging real-time traffic data sets, and experimenting with more sophisticated algorithms such as PPO OR SAC for better generalization. On top of this, enhancing the reward function to include environmental and economic factors can provide a better-balanced framework towards integration with smart cities.

Overall, the research gives a computationally sound, adaptive, and scalable solution to traffic light optimization that opens the doors for integrating AI-based traffic systems into smart cities.

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