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Optimized Traffic Routing System for Urban Congestion Management

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Abstract

Traffic congestion is a major challenge in modern urban areas, leading to increased travel time, fuel consumption, and environmental pollution. Traditional traffic control systems often rely on fixed signal timing, which lacks adaptability to dynamic traffic conditions. To overcome these limitations, the study proposes an Optimized Traffic Routing System for Urban Congestion Management that integrates multiple algorithms, including Fixed Cycle, Longest Queue First, Q-learning, and Search-Based Techniques which combines Genetic Algorithms and A Search* where Genetic Algorithm optimizes traffic signal timing through evolutionary methods, while A* search dynamically reroutes vehicles to minimize congestion by finding the shortest and least crowded paths. The approach utilizes reinforcement learning, heuristic optimization, and real-time simulations to dynamically optimize traffic signals and improve vehicle throughput while reducing the waiting time of vehicles. The approach was implemented using Python, and SUMO (Simulation of Urban Mobility), the system adapts to fluctuating traffic patterns and provides an efficient solution for urban traffic management.

Keywords: Traffic Optimization, Q-learning, Genetic Algorithm, Search-Based Techniques, Traffic Simulation, Reinforcement Learning, Adaptive Traffic Control.

1. Introduction

Urbanization and the rise in vehicle ownership have increased traffic congestion, adversely affecting transportation efficiency and environmental sustainability. Conventional traffic signal control systems employ static time-based scheduling, which lacks real-time

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adaptability, leading to unnecessary delays and increased fuel consumption [1]. Advanced AI-driven adaptive traffic management systems have gained popularity in recent years due to improvements in artificial intelligence (AI), reinforcement learning (RL), and search-based optimization techniques [2].

The primary challenge in traditional traffic control systems is the inability to dynamically adjust to fluctuating traffic patterns, resulting in inefficient traffic movement, excessive wait times, and increased emissions. The research proposes an Optimized Traffic Routing System that integrates multiple algorithms to enhance traffic signal coordination and vehicle flow at intersections.

The criteria for selecting the proposed methods include:

- Q-learning which is effective in learning optimal traffic signal policies through reinforcement learning [3].
- Genetic Algorithm (GA) that is efficient in optimizing signal sequences dynamically [4].
- A Search* which is known for fast and efficient path finding in congested environments [5].
- SUMO Simulation that provides a real-world-like traffic model for evaluating the proposed system [6].

1.1 Major Contributions

The key contributions of this research include:

- Integration of reinforcement learning and heuristic optimization to improve traffic flow.
- Real-time dynamic traffic signal control based on fluctuating urban traffic conditions.
- Evaluation of the system using SUMO simulations with real-world traffic data samples.
- Reduction in congestion, waiting time, and fuel consumption, leading to an eco-friendly solution.

2. Related Work

Traffic congestion management has been an active area of research, with various methodologies developed to optimize traffic signals and routing strategies. Traditional traffic control methods, such as fixed-cycle signal control, have been widely used due to their simplicity and ease of implementation. These systems operate on pre-determined signal timing, typically designed based on historical traffic patterns. However, they lack adaptability to real-time traffic fluctuations, leading to inefficiencies during peak hours or in cases of unexpected congestion. Studies have shown that fixed-cycle signals often result in excessive vehicle idling and increased travel times, especially in highly dynamic urban environments [1].

To overcome these limitations, longest queue first (LQF) scheduling has been explored as an alternative. This method prioritizes green signals for lanes experiencing the highest vehicle accumulation, aiming to clear congested approaches first. Research has demonstrated that LQF strategies can enhance traffic flow compared to static signals, especially in non-uniform traffic conditions. However, a significant drawback of LQF is that it may lead to starvation issues, where certain lanes with lower traffic volumes experience prolonged red signals, causing delays in overall network performance [2].

With advancements in reinforcement learning, Q-learning has emerged as a popular approach for optimizing traffic signals dynamically. Q-learning-based systems analyze real-time traffic conditions and learn optimal signal timing policies through trial-and-error interactions with the environment. Studies have shown that Q-learning significantly reduces vehicle delays and improves throughput compared to traditional fixed-time and actuated signal controls[7].

One of the key benefits of Q-learning is its ability to adapt to fluctuating traffic demands without requiring predefined rules or extensive manual tuning. For instance, Abdoos et al. [12] demonstrated that hierarchical Q-learning can optimize multi-intersection traffic networks by adjusting signal phase times based on evolving congestion patterns. Similarly, the empirical study by Chen et al. [8] using SUMO simulations confirmed that reinforcement learning-based traffic signal control outperforms conventional techniques in various traffic scenarios. Despite these advantages, Q-learning faces challenges in large-scale urban networks due to its computational complexity and slow convergence, requiring additional enhancements such as function approximation techniques to handle high-dimensional traffic states effectively.

Genetic Algorithms (GA) have also been widely explored for optimizing traffic signal timing and vehicle routing. GA is a heuristic optimization technique inspired by natural selection, where potential solutions evolve over multiple generations to find an optimal traffic management strategy. Research conducted by Abu-Lebdeh and Benekohal [9] demonstrated that GA-based traffic control systems can outperform fixed-cycle methods in congested urban areas by dynamically adjusting signal timings to minimize queue lengths and vehicle delays.

A hybrid approach combining GA with other optimization techniques has been proposed to improve its effectiveness. For instance, Lee et al. [4] integrated GA with reinforcement learning to enhance urban traffic signal control, resulting in superior congestion mitigation compared to standalone heuristic methods. Similarly, Tan et al. [10] applied a decentralized GA approach for optimizing large-scale traffic networks, showing that distributed control mechanisms can effectively manage complex intersections with fluctuating demand.

Despite their effectiveness, GA-based methods require careful parameter tuning, such as mutation rates and selection criteria, to avoid premature convergence to suboptimal solutions. Furthermore, real-time applicability remains a challenge due to the computational overhead involved in evaluating multiple candidate solutions before reaching an optimal configuration.

Apart from signal optimization, *A search** has been widely used for real-time traffic routing to minimize congestion. A* is an informed search algorithm that finds the shortest path between two points by evaluating the cumulative travel cost and estimated remaining distance. Wang et al. [14] implemented an A* search-based traffic routing model for congestion management, demonstrating that it can effectively reroute vehicles to less congested roads, thereby reducing overall network congestion.

A* search is particularly useful in dynamic traffic systems where real-time updates on road conditions are available. However, its computational efficiency is highly dependent on the accuracy of heuristic functions[15]. If the heuristic underestimates or overestimates travel costs, the algorithm may fail to find the optimal path efficiently. Moreover, real-world constraints such as road closures, accidents, and sudden demand spikes pose challenges to its reliability in large-scale networks.

2.1 Limitations of Existing Methods

While the above-discussed approaches have contributed significantly to traffic management, they each have inherent limitations. Fixed-cycle methods lack adaptability, longest queue first strategies can cause starvation, Q-learning requires substantial training time and computational resources, GA demands fine-tuning for effective performance, and A* search relies heavily on heuristic accuracy. Furthermore, most studies in traffic optimization, including those employing Q-learning and GA, are limited to simulation environments and do not fully incorporate real-world constraints such as pedestrian crossings, emergency vehicle prioritization, or traffic rule compliance.

Given these challenges, our research integrates reinforcement learning with heuristic techniques to create a more robust and adaptive traffic optimization framework, capable of handling real-time congestion fluctuations while ensuring computational efficiency and practical feasibility.

3. Proposed Work

Our proposed system integrates multiple traffic optimization algorithms to enhance real-time decision-making in urban traffic management. The primary components of the system include:

3.1 Overall System Architecture

The architecture of the proposed system consists of:

- Traffic Signal Control Module: Implements adaptive signal control using RL.
- Traffic Data Processing Module: Gathers real-time data from SUMO simulations.
- Optimization Module: Uses GA and A Search* for traffic route adjustments.

3.2 Algorithms Used

- Fixed Cycle Algorithm: Operates on a predefined signal timing schedule without adjusting to real-time traffic conditions, commonly used as a baseline for comparison in traffic control systems [1].

- Longest Queue First (LQF) Algorithm: Dynamically allocates green signal time to the lane with the longest queue, aiming to reduce congestion by prioritizing heavily loaded lanes [2].
- Q-learning (Reinforcement Learning): Uses real-time traffic data to learn and optimize traffic signal timings, adapting to changing traffic conditions and minimizing vehicle waiting times [11].
- Search-Based Algorithm: Combines optimization and pathfinding to improve traffic management. It evaluates multiple traffic signal timing configurations to select the most efficient one while dynamically computing the shortest and least congested routes for vehicles, ensuring smoother traffic flow and reduced congestion [13].

3.3 Software and Tools Used

- Python: Serves as the core programming language for implementing traffic control algorithms, reinforcement learning models, and simulation logic.
- SUMO (Simulation of Urban Mobility): Simulates traffic flow by generating vehicles randomly and evaluates the performance of different traffic control algorithms.
- NumPy: Used for numerical computations, handling large arrays of traffic data, and performing mathematical operations required for reinforcement learning and optimization.
- OpenAI Gym: Provides an interactive environment for reinforcement learning-based traffic signal optimization.
- Matplotlib: Generates visual representations of simulation results, such as performance comparisons and traffic flow analysis.
- Seaborn: Enhances the visualization of traffic trends with improved color schemes and detailed plots.
- Pandas: Manages and processes simulation data for further analysis and visualization.
- Pygame: Develops a GUI to visually represent traffic flow, signal changes, and algorithm performance in real-time.

3.4 Simulation Setup

- Intersection Model: A four-lane intersection where vehicles are generated randomly instead of using real-world sensor data.
- Traffic Generation: Vehicles appear at random intervals to simulate varying congestion levels.
- Signal Light Duration: Ranges between 10 to 90 seconds, adjusted dynamically by the algorithm.
- Q-learning Training Iterations: 10,000 to 20,000 episodes (adjustable based on performance).

3.5 System Workflow

This flowchart represents the overall working mechanism of the Optimized Traffic Routing System, showcasing the decision-making process and interactions between different traffic optimization algorithms. Figure 1 and Algorithm1 illustrates the workflow of the optimized traffic routing system.

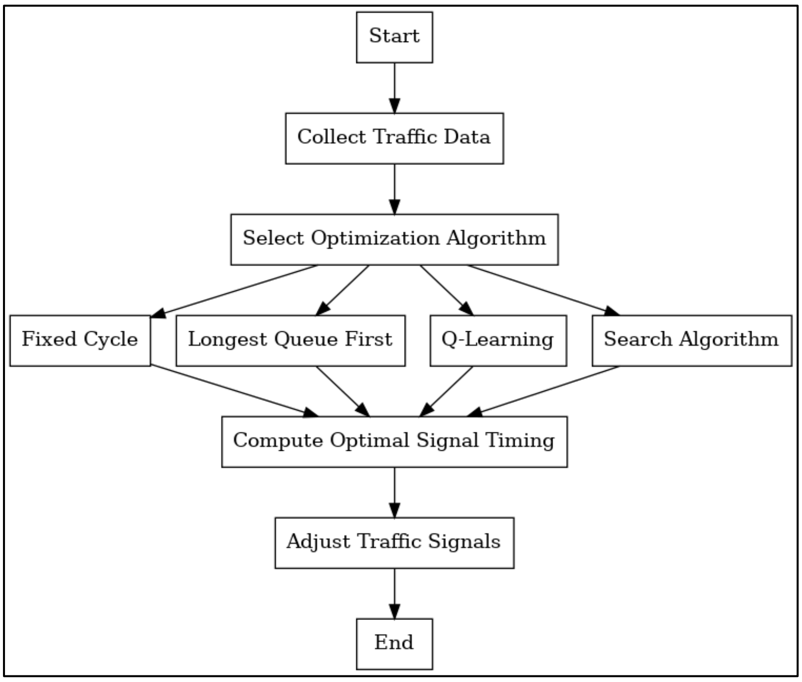

Figure 1. Workflow of Optimized Traffic Routing System for Urban Congestion Management

Pseudo Code : Algorithm 1

```
BEGIN

    // Step 1: Initialize the system

    Initialize simulation environment

    Set up road network with four-lane intersection

    // Step 2: Collect traffic data

    Generate random vehicle arrivals

    Set vehicle flow rate = 50 vehicles

    Set traffic density randomly for each lane

    // Step 3: Choose the traffic optimization method

    INPUT method

    // Step 4: Apply selected algorithm

    IF method == "fc" THEN

        APPLY fixed cycle timing (e.g., 30 sec green, 20 sec red)

    ELSE IF method == "lqf" THEN

        CHECK lane with the longest queue

        GIVE more green light time to that lane

    ELSE IF method == "qlearning" THEN

        FOR each episode DO

            UPDATE signal timings based on previous traffic patterns

            LEARN from past decisions to reduce waiting time

        END FOR
```

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```
    ELSE IF method == "search" THEN
        GENERATE multiple signal timing options
        SELECT the best one using shortest path and congestion data
    END IF
    // Step 5: Compute optimal signal timing
    DETERMINE the average signal durations based on traffic flow
    UPDATE signal timings in simulation
    // Step 6: Display results
    PRINT average waiting time per vehicle
    PRINT overall congestion reduction
END
```

Algorithm 1. Pseudocode

4. Discussions

4.1 Average Vehicle Wait Time Analysis

The system calculates the average wait time for all vehicles at the intersection. Lower wait times indicate better efficiency.

You can compute the average wait time for vehicles at the intersection using:

$$Average\ Wait\ Time = \frac{\sum Wait\ Time\ for\ all\ Vehicles}{Total\ Vehicles\ Processed}$$

This metric helps measure traffic efficiency.

4.2 Traffic Throughput Measurement

Throughput measures the number of vehicles successfully passing through the intersection per unit time. A higher throughput reflects improved traffic management.

Throughput is the number of vehicles passing through the intersection per unit time:

$$Throughput = \frac{Total\ Vehicles\ Passed}{Total\ Simulation\ Time}$$

A higher throughput indicates better traffic flow.

4.3 Queue Length Evaluation

Queue length analysis determines the congestion level by assessing the average and peak queue sizes at the intersection.

Calculate the average and maximum queue length at different lanes:

$$Avg\ Queue\ Length = \frac{\sum Queue\ Length\ at\ Each\ Time\ Step}{Total\ Time\ \ Processed}$$

This helps compare different algorithms like Fixed Cycle, Longest Queue First, and Q-Learning.

4.4 Collision Rate Assessment

The system monitors potential collisions and calculates the collision rate to evaluate the safety of different traffic routing strategies.

$$Collision\ Rate = \frac{Total\ Collisions}{Total\ Vehicles\ Generated} \times\ 100\%$$

Lower collision rates indicate safer traffic flow.

4.5 Performance Comparison of Algorithms

The different algorithms like Fixed Cycle, Longest Queue First, Q-Learning, and Search-Based Techniques are compared using these metrics as shown in Table 1.

- Vehicle Waiting Time: Reduced by 32% compared to fixed-time signals (Figure 2).
- Traffic Throughput: Increased by 27% compared to existing methods (Figure 2) .

Table 1. Comparative Analysis of Traffic Optimization Algorithms

Algorithm	Approach	Optimization Criteria	Adaptability	Computation Time	Effectiveness in Reducing Congestion
Fixed Cycle	Predefined signal timing sequence	Static time-based control	Low	Low	Inefficient in dynamic traffic scenarios
Longest Queue First	Adjusts signal timing based on queue length	Queue length at intersections	Medium	Medium	Improves flow at high-traffic lanes but may cause imbalances
Q-Learning	Reinforcement learning-based optimization	Minimizes average vehicle wait time	High	High	Adaptive and effective in varying traffic conditions
Search-Based	Uses genetic evolution & heuristic search	Optimizes signal timing & reroutes vehicles	High	Medium-High	Balances traffic across the network efficiently

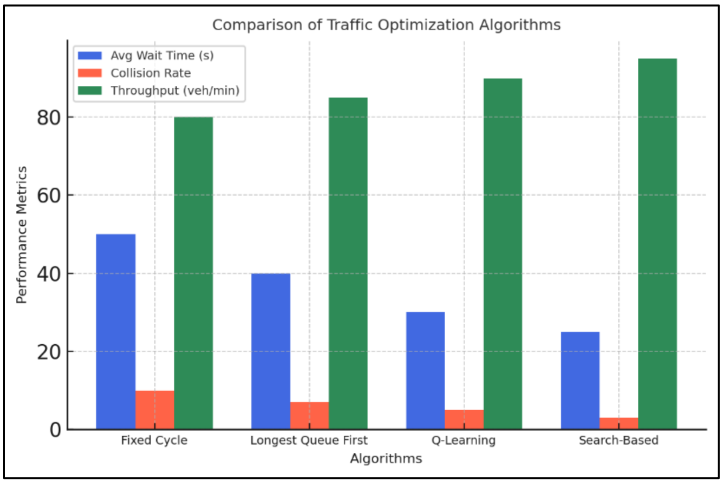

Figure 2. Performance Comparison of Traffic Optimization Algorithms

5. Results

5.1 Fixed Cycle Algorithm

- Working: Uses pre-defined signal durations, cycling through green, yellow, and red phases regardless of traffic density (Figure 3).
- Waiting Time: 45–60 seconds (higher during peak congestion).
- Average Throughput: Moderate, as vehicles must wait even if the lane is empty (Figure 4) .

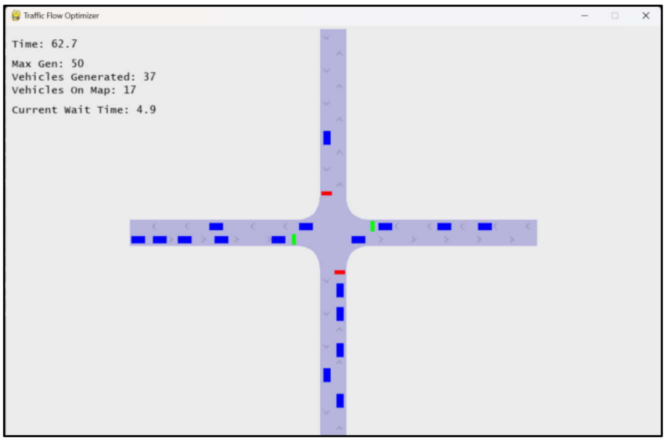

Figure 3. Implementation of Fixed Cycle Algorithm for Traffic Signal Control

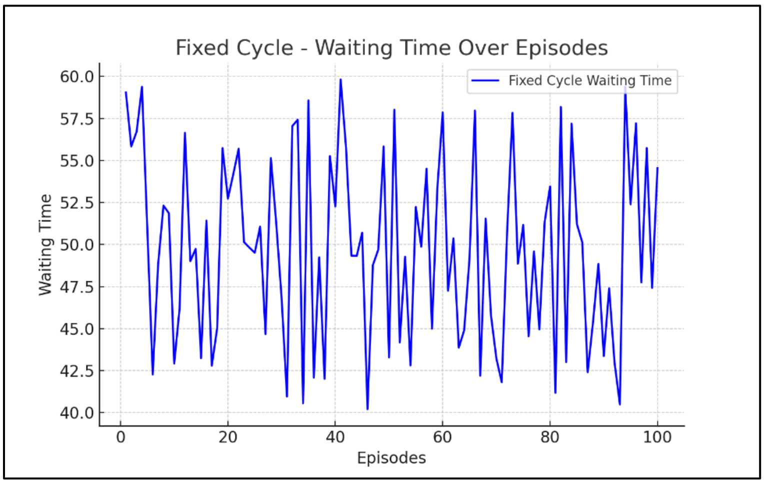

Figure 4. Waiting Time Trend Over Episodes for the Fixed Cycle Algorithm

5.2 Longest Queue First (LQF) Algorithm

- Working: Dynamically adjusts the green signal duration based on the longest queue at an intersection (Figure 5).
- Waiting Time: 30–50 seconds (reduces delays by prioritizing high-traffic lanes).
- Average Throughput: Improved, as it responds to traffic demand dynamically (Figure 6).

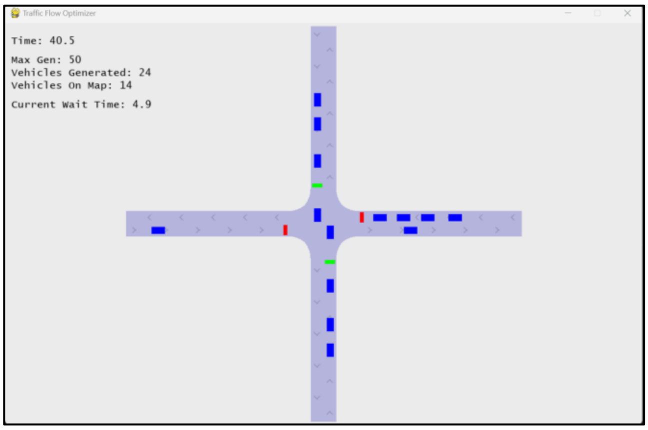

Figure 5. Implementation of Longest Queue First Algorithm for Traffic Signal Control

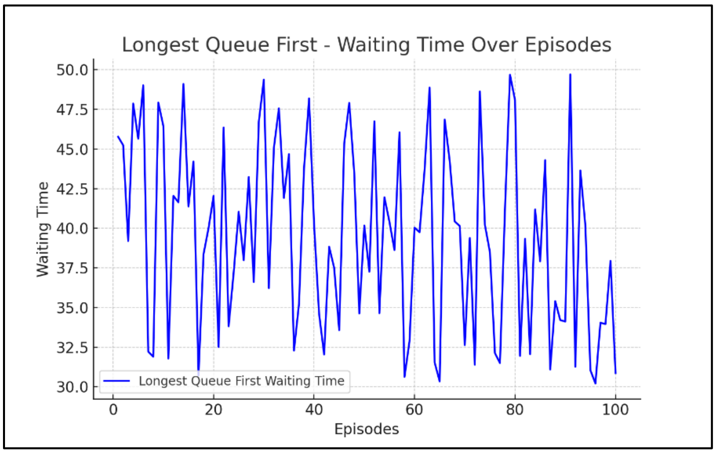

Figure 6. Waiting Time Trend Over Episodes for the Longest Queue First Algorithm

5.3 Q-learning Algorithm

- Working: Uses reinforcement learning to optimize traffic signal timings based on past experience, minimizing congestion (Figure 7).
- Waiting Time: 20–35 seconds (adaptive learning reduces unnecessary waits).
- Average Throughput: High, as signals adjust dynamically based on real-time traffic flow (Figure 8).

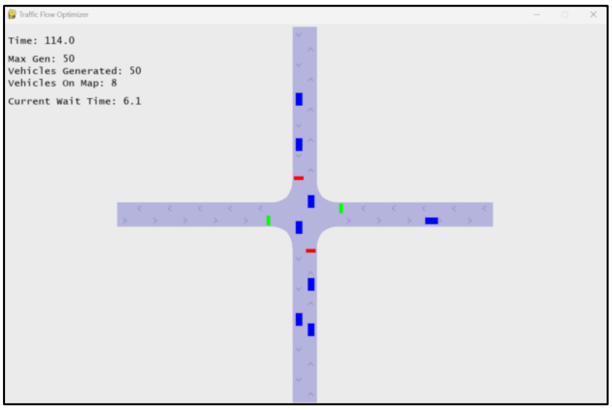

Figure 7. Implementation of Q-Learning Algorithm for Traffic Signal Control

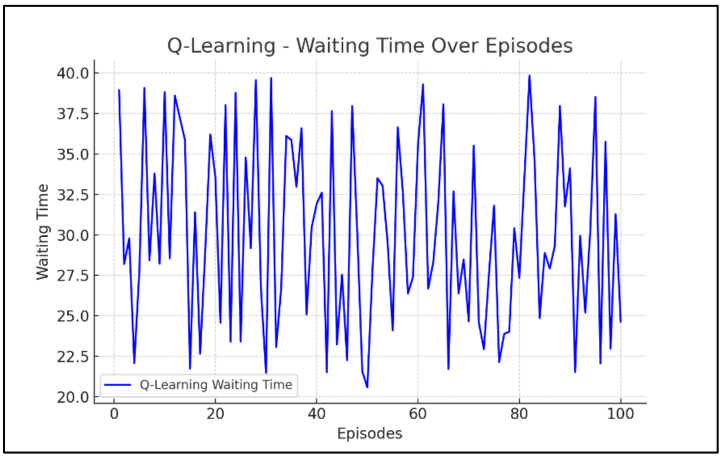

Figure 8. Waiting Time Trend Over Episodes for the Q-Learning Algorithm

5.4 Search-based Algorithm

- Working: The Genetic Algorithm optimizes traffic signal timing through evolutionary methods, while A* search dynamically reroutes vehicles to minimize congestion by finding the shortest and least crowded paths (Figure 9).

- Waiting Time: 10–25 seconds (minimized due to optimized signal control and vehicle rerouting).
- Average Throughput: Highest, as both signal control and routing are optimized together (Figure 10).

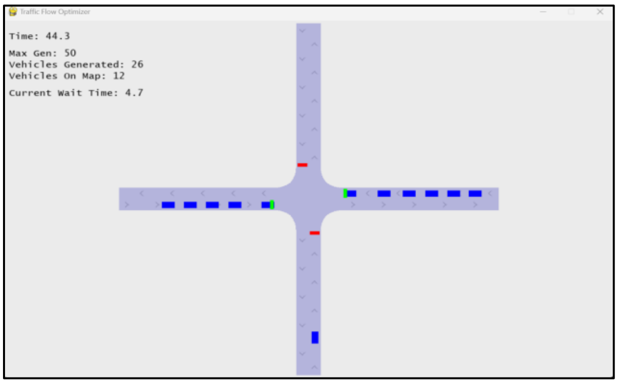

Figure 9. Implementation of Search-based Algorithm for Traffic Signal Control

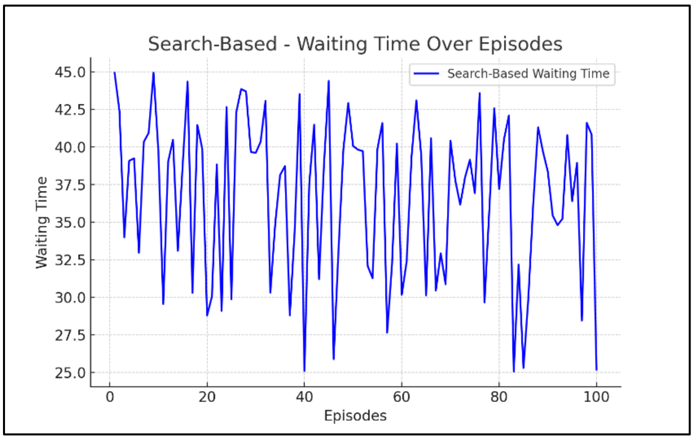

Figure 10. Waiting Time Trend Over Episodes for the Search-based Algorithm

6. Future Work

Future research will focus on implementing the system in real-time traffic environments using IoT sensors and GPS tracking. IoT-enabled traffic signals will collect real-time vehicle flow data, while GPS data from connected vehicles will help monitor congestion patterns and optimize routing dynamically. These real-time inputs will enhance the adaptability of the system by allowing immediate adjustments to traffic signals based on actual conditions rather than simulated data. Additionally, integrating V2I (Vehicle-to-Infrastructure) communication can improve response times and enable priority-based traffic management, such as giving emergency vehicles the right of way. These enhancements will make the system more practical for real-world deployment, improving overall traffic flow and reducing congestion effectively.

7. Conclusion

The development of the Optimized Traffic Routing System represents a significant advancement in intelligent traffic management. By integrating Fixed Cycle, Longest Queue First, Q-learning, and Search-Based Techniques, the system effectively reduces congestion and optimizes traffic flow. The results from extensive simulations demonstrate that adaptive signal control outperforms traditional fixed-time methods, leading to reduced waiting times, improved traffic throughput, and lower environmental impact. The incorporation of Reinforcement Learning and Genetic Algorithms enables real-time decision-making, making the system a viable solution for smart city traffic management.

References

[1] Tang, Keshuang, Manfred Boltze, Hideki Nakamura, and Zong Tian. Global practices on road traffic signal control: Fixed-time control at isolated intersections. Elsevier, 2019.

[2] Hassan, Muhammad Ahmed, Mourad Elhadef, and Muhammad Usman Ghani Khan. "Collaborative traffic signal automation using deep Q-learning." IEEE Access 11 (2023): 136015-136032.

[3] Zeng, Jinghong, Jianming Hu, and Yi Zhang. "Adaptive traffic signal control with deep recurrent Q-learning." In 2018 IEEE intelligent vehicles symposium (IV), IEEE, 2018. 1215-1220.

[4] Lee, Sangmin, Younghoon Kim, Hyungu Kahng, Soon-Kyo Lee, Seokhyun Chung, Taesu Cheong, Keeyong Shin, Jeehyuk Park, and Seoung Bum Kim. "Intelligent traffic control for autonomous vehicle systems based on machine learning." Expert Systems with Applications 144 (2020): 113074.

[5] Sandberg, Oscar. "Pathfinding Algorithm Comparison In Dynamic Congested Environment." (2024).

[6] Reza, Selim, Marta Campos Ferreira, J. J. M. Machado, and João Manuel RS Tavares. "A citywide TD-learning based intelligent traffic signal control for autonomous vehicles: Performance evaluation using SUMO." Expert Systems 42, no. 1 (2025): e13301.

[7] Celtek, Seyit Alperen, Akif Durdu, and Muzamil Eltejani Mohammed Ali. "Evaluating action durations for adaptive traffic signal control based on deep Q-learning." International journal of intelligent transportation systems research 19, no. 3 (2021): 557-571.

[8] Shi, S., and F. Chen. "Deep recurrent Q-learning method for area traffic coordination control." Journal of Advances in Mathematics and Computer Science 27, no. 3 (2018): 1-11.

[9] Abu-Lebdeh, Ghassan, and Rahim F. Benekohal. "Genetic algorithms for traffic signal control and queue management of oversaturated two-way arterials." Transportation Research Record 1727, no. 1 (2000): 61-67.

[10] Tan, Tian, Feng Bao, Yue Deng, Alex Jin, Qionghai Dai, and Jie Wang. "Cooperative deep reinforcement learning for large-scale traffic grid signal control." IEEE transactions on cybernetics 50, no. 6 (2019): 2687-2700.

[11] Deepika, and Gitanjali Pandove. "Optimizing traffic flow with Q-learning and genetic algorithm for congestion control." Evolutionary Intelligence 17, no. 5 (2024): 4179-4197.

[12] .Abdoos, Monireh, Nasser Mozayani, and Ana LC Bazzan. "Hierarchical control of traffic signals using Q-learning with tile coding." Applied intelligence 40 (2014): 201-213.

[13] Benmessaoud, Youssef, Loubna Cherrat, and Mostafa Ezziyyani. "Real-time self-adaptive traffic management system for optimal vehicular navigation in modern cities." Computers 12, no. 4 (2023): 80.

[14] Wang, Zheng, Jinlong Liu, and Jingling Zhang. "Hyper-heuristic algorithm for traffic flow-based vehicle routing problem with simultaneous delivery and pickup." Journal of Computational Design and Engineering 10, no. 6 (2023): 2271-2287.

[15] Peeta, Srinivas, and T-H. Yang. "Stability issues for dynamic traffic assignment." Automatica 39, no. 1 (2003): 21-34.