ALCOM:
Journal of Algorithm & Computing
Journal homepage: https://alcom.id

An Efficient Graph-Based Algorithm for Real-Time Traffic Flow Optimization in Smart Cities

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ARTICLE INFO

Article history:
Received : 08/02/2025
Revised : 09/02/2025
Accepted : 09/02/2025
Available online 10/02/2025

E-ISSN:
P-ISSN:

How to cite:
Purnamasari, E., Nurwildani, M.F. "An Efficient Graph-Based Algorithm for Real-Time Traffic Flow Optimization in Smart Cities," Journal of Algorithm & Computing, vol. 01, no. 01, February 2025, doi: xx.xxxxx/alcom.xxxxxx.

ABSTRACT

With the rapid increase in vehicle density, urban traffic congestion has become a significant challenge, leading to inefficiencies in transportation systems and increased fuel consumption. Existing traffic management methods, such as fixed signal timing and heuristic-based optimizations, struggle to adapt to real-time traffic fluctuations. While recent studies have explored graph-based models and reinforcement learning for traffic optimization, they often fail to capture complex spatiotemporal dependencies dynamically. To address this gap, we propose a novel graph-based algorithm that integrates spatiotemporal graph convolutional networks (ST-GCN) with reinforcement learning techniques. The algorithm dynamically adjusts traffic signals, reroutes vehicles, and provides real-time guidance based on sensor and environmental data. Experimental evaluations using a simulated urban traffic environment demonstrate that our approach significantly reduces vehicle waiting times and improves overall traffic flow compared to traditional methods. These findings highlight the potential of adaptive, intelligent traffic management systems for smart cities.

Keyword: Graph-Based Algorithm, Traffic Flow Optimization, Smart Cities, Reinforcement Learning, Spatiotemporal Networks

1. INTRODUCTION

The rapid increase in urban vehicle density has resulted in significant traffic congestion, which poses substantial challenges for transportation management in contemporary cities. Traditional traffic control systems predominantly utilize fixed signal timing schemes that lack the ability to adapt dynamically to changing traffic conditions. This rigidity leads to prolonged vehicle delays, increased fuel consumption, and higher greenhouse gas emissions [1]. The advent of smart city initiatives has underscored the necessity for intelligent and adaptive traffic management solutions that harness real-time data analytics and artificial intelligence (AI) [2][3]. Recent advancements in sensor networks, the Internet of Things (IoT), and machine learning techniques present promising opportunities for optimizing urban traffic flow through data-driven decision-making [4][5].

Conventional traffic management systems are often inadequate in responding to dynamic traffic patterns, resulting in inefficiencies in urban mobility [6]. Existing methods, such as rule-based signal adjustments and pre-programmed traffic light sequences, frequently falter in highly dynamic environments where congestion levels fluctuate due to unforeseen events like accidents or adverse weather conditions [7]. While machine learning models have been developed for traffic forecasting, many current implementations struggle to effectively integrate real-time traffic data with adaptive decision-making mechanisms [8]. The challenge remains in creating a traffic optimization algorithm that not only predicts congestion but also dynamically adjusts traffic control measures to enhance flow in real-time [9].

The integration of AI into urban transportation systems has been highlighted as a critical step towards alleviating the pressures of rising traffic volumes in expanding cities [4]. For instance, the use of IoT-enabled sensor networks facilitates real-time data collection on traffic conditions, which can be analyzed to inform traffic signal adjustments and routing decisions [10]. Furthermore, machine learning techniques can automate traffic management processes, enabling systems to learn from historical data and adapt to current conditions, thereby improving overall traffic efficiency [6]. The development of intelligent traffic systems that leverage these technologies is essential for addressing the complexities of urban mobility and enhancing the sustainability of transportation networks [2][5].

The increasing complexity of urban traffic systems necessitates the development of advanced traffic management solutions that can effectively address several critical challenges. Among these challenges are the limited adaptability to real-time data, inefficient representation of traffic flow, computational complexity of optimization models, and the lack of integration between traffic signal control and vehicle routing.

Many existing traffic management models struggle to integrate real-time sensor data effectively, which is crucial for optimizing performance in dynamic environments. Traditional systems often rely on static signal timings and historical data, which can lead to suboptimal traffic management during peak hours or unexpected events [11]. For instance, Laanaoui emphasizes the importance of real-time anomaly detection and load balancing in enhancing urban traffic management, highlighting the shortcomings of models that do not adapt to real-time conditions [12]. Similarly, Moumen discusses the integration of IoT data and AI to improve urban mobility, indicating that many current systems fail to leverage real-time data effectively [3].

The representation of traffic flow in traditional models often fails to capture the complex spatiotemporal dependencies inherent in transportation networks. This inefficiency can significantly reduce the accuracy of traffic predictions and the overall effectiveness of traffic management strategies [13]. Rajalakshmi and S discuss hybrid time-series forecasting models that aim to improve traffic flow predictions, yet traditional models still struggle with accurately modeling the dynamic nature of urban traffic [14]. Additionally, Lim's research on enhancing real-time traffic volume prediction demonstrates the need for adaptable methodologies that can respond to varying road conditions [15].

The computational demands of reinforcement learning models used in traffic optimization present significant barriers to their deployment in large-scale urban settings. These models often require extensive computational resources, making them impractical for real-time applications [16]. For example, research by Kim et al. highlights the challenges associated with real-time traffic signal optimization using advanced algorithms, which can be resource-intensive [17]. Furthermore, Zhou et al. discuss the need for efficient algorithms that can operate within the constraints of real-world traffic systems while minimizing computational overhead [18].

A significant gap in current traffic management strategies is the lack of integration between traffic signal control and vehicle routing systems. Many existing models focus exclusively on optimizing either signal timing or vehicle routing, neglecting the potential benefits of a holistic approach that considers both aspects simultaneously [11]. For instance, Zhao emphasizes the importance of coordinated control strategies that can dynamically adjust traffic signals based on real-time vehicle routing data [19]. Similarly, research by Alsharman illustrates how machine learning techniques can be employed to enhance traffic light management by integrating various traffic parameters [20].

To bridge these gaps, this research presents a novel graph-based algorithm that integrates spatiotemporal graph convolutional networks (ST-GCN) with reinforcement learning (RL) techniques. This hybrid approach aims to: a) Construct a dynamic spatiotemporal graph representation of traffic networks to better capture interdependencies between road segments, intersections, and congestion patterns; b) Leverage graph convolutional networks (GCNs) to extract essential traffic features from real-time data sources, including traffic sensors, vehicle trajectories, and environmental conditions; c) Utilize reinforcement learning to dynamically adjust traffic signal timings, reroute vehicles, and provide real-time personalized guidance to drivers; d) Optimize traffic flow efficiency by minimizing travel delays, fuel consumption, and vehicle idle times through an adaptive, self-learning system.

The subsequent sections of this paper are structured as follows: Section 2 explains the proposed graph-based optimization framework, including graph construction, feature extraction, and reinforcement learning integration. Section 3 describes the experimental framework used for validation and presents performance comparisons with traditional models. Section 4 analyzes key findings, implications, and potential improvements to the proposed approach. Finally, Section 5 summarizes the study's contributions and outlines future research directions for further enhancement of real-time traffic optimization models.

2. METHODOLOGY

To address the limitations of existing traffic optimization methods, this research introduces a graph-based traffic optimization algorithm that integrates Spatiotemporal Graph Convolutional Networks (ST-GCN) and Reinforcement Learning (RL) techniques. The methodology consists of three key components: graph construction, feature extraction, and real-time optimization.

2.1. Graph Construction

A spatiotemporal graph is built to model the urban traffic network, capturing both spatial relationships (road connections, intersections) and temporal dependencies (traffic flow changes over time). Graph construction is a crucial step in modeling an urban traffic network for real-time optimization. It transforms raw traffic data into a structured graph representation, capturing both spatial (road connections, intersections) and temporal (traffic flow evolution) dependencies. This structured representation enables efficient processing using Graph Neural Networks (GNNs) and Spatiotemporal Graph Convolutional Networks (ST-GCNs).

A traffic network is modeled as a spatiotemporal graph $G = (V, E)$, where: V is the set of nodes, representing road segments and intersections. E is the set of edges, capturing both: spatial edges E_s (road connections), and temporal edges E_t (historical traffic dependencies). Each node v_i has associated feature vectors X_i, representing real-time traffic data. The adjacency matrix A is constructed to define connectivity:

$$A_{ij} = \begin{cases} 1, & if\ any\ connection\ between\ v_i\ and\ v_j \\ 0, & otherwise \end{cases}$$

Real-time and historical traffic data are used to construct G. We are using dataset from [21] to achieve traffic sensors data such as real-time vehicle count, speed, congestion levels. Also GPS data such as vehicle trajectories, road usage patterns. To construct the spatiotemporal traffic graph, we define a step-by-step pseudo-code that describes the graph creation process:

ALGORITHM 1: GRAPH CONSTRUCTION

```
BEGIN
    LOAD traffic dataset from real-time sensors and historical records
    CREATE an empty directed graph G
    FOR each record in dataset:
        EXTRACT Road_ID, Vehicle_Count, Avg_Speed, and Congestion_Level
        ADD Road_ID as a node in G with attributes (Vehicle_Count, Avg_Speed)
    DEFINE a set of SPATIAL EDGES (E_s) connecting road segments based on road network topology
    ADD these spatial edges to G
    FOR each node in G:
        ADD TEMPORAL EDGES (E_t) using historical congestion trends
        SET node attribute Historical_Trend based on past traffic data
    RETURN the constructed spatiotemporal graph G
END
```

To capture dynamic traffic conditions, the node features are updated using spatiotemporal graph embedding:

$$X_i^t = f(X_i^{t-1}, N(X_i), \Theta) \quad (1)$$

where X_i^t is the updated feature vector at time t, $N(X_i)$ represents neighboring nodes' influence, and Θ

are trainable model parameters for feature transformation. The edge weights w_{ij} are determined based on real-time congestion levels:

$$w_{ij} = \frac{1}{1 + e^{-\beta(c_j - c_i)}} \tag{2}$$

where c_i, c_j are congestion levels of nodes i, j, and β is a tunable parameter controlling sensitivity.

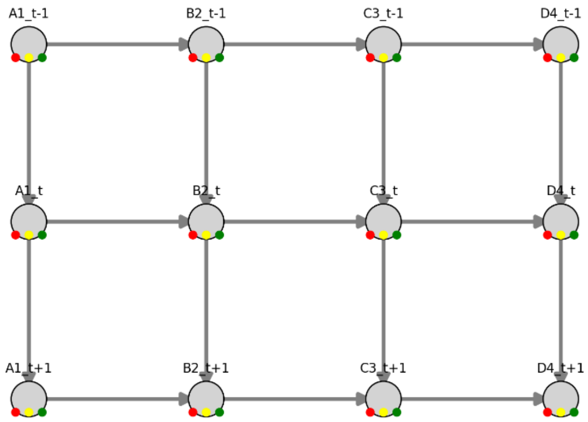

Fig. 1. Enhanced Spatio-temporal traffic network

Figure 1 depict the spatio-temporal traffic network that consist of two types of coonection, namely spacial edges which connect road segments based on physical roads and temporal edges which capture historical traffic dependencies at different time intervals. Each node (A1, B2, C3, D4, etc.) represents a road segment or intersection, while the subscript tt denotes time, meaning a road segment is monitored at different time intervals. The spatial edges E_s represented by horizontal link define physical road connections, and the temporal edges E_t represented by vertical line link the same road segment across different time steps.

2.2. Feature Extraction with Graph Convolutional Networks (GCNs)

Once the traffic network is represented as a spatiotemporal graph, the next crucial step is feature extraction. This process transforms raw traffic data into meaningful patterns that can be used for real-time optimization. Graph Convolutional Networks (GCNs) are employed to extract spatial and temporal dependencies from the constructed traffic graph. Unlike traditional convolutional networks, which operate on Euclidean data (e.g., images), GCNs are specifically designed to process non-Euclidean structures, such as traffic networks, where road segments and intersections are interconnected dynamically.

Traffic networks exhibit complex spatial and temporal correlations such as: spatial dependency which means nearby road segments influence each other. For instance, congestion on A1 may affect B2, C3, and further roads downstream. Also the temporal dependency that means traffic conditions fluctuate over time. A congestion event at 8:00 AM may cause ripple effects at 8:10 AM and beyond.

GCNs efficiently model both dependencies by aggregating traffic information from neighboring nodes while preserving the network structure. This allows the system to predict congestion, detect anomalies, and optimize signal timing dynamically. A Graph Convolutional Network (GCN) updates node features by aggregating information from neighboring nodes. Mathematically, this is expressed as:

$$H^{l+1} = \sigma\left(D^{-\frac{1}{2}} A D^{-\frac{1}{2}} H^{(l)} W^{(l)}\right) \tag{3}$$

where H^L is the feature matrix at layer l, A is the adjacency matrix of the graph, D is the degree matrix (sum of connections per node), $W^{(l)}$ is the trainable weight matrix at layer l, and σ is an activation function (e.g., ReLU). This operation allows each node to update its representation based on neighboring nodes, ensuring that the learned features incorporate both spatial and temporal information.

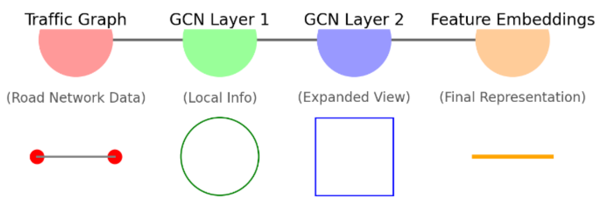

Fig. 2 Pipeline of feature extraction

The feature extraction pipeline consists of three main stages. The first is input representation., each road segment (node) is associated with traffic-related attributes, such as vehicle count, average speed, congestion level, and historical flow trends. Second, the GCN propagates and aggregates information across the road network and also each node updates its traffic feature vector by considering its connected roads. Finally, the extracted features are used as inputs for optimization models (e.g., reinforcement learning for signal control), these would help predicting congestion hotspots and suggesting dynamic adjustments.

2.3. Real-Time Traffic Optimization with Reinforcement Learning (RL)

After constructing the spatiotemporal traffic graph and extracting meaningful features using Graph Convolutional Networks (GCNs), the next step is to optimize traffic flow in real-time. This study employs Reinforcement Learning (RL) as the primary approach for traffic signal control and vehicle rerouting. Unlike traditional rule-based traffic systems that rely on fixed signal timings, RL enables adaptive and self-learning mechanisms that adjust dynamically based on real-time congestion levels. The goal is to minimize vehicle waiting times, reduce travel delays, and improve fuel efficiency by continuously learning from traffic patterns.

Traditional traffic management techniques, such as fixed-timing signals and heuristic-based optimizations, fail to adapt to fluctuating traffic conditions. These methods often result in suboptimal performance, especially during unexpected congestion spikes. Reinforcement Learning (RL) solves this issue by continuously learning and updating traffic control policies based on feedback from the environment. The RL model interacts with traffic data, observes congestion trends, and dynamically optimizes signal timings and vehicle routing in a way that maximizes overall traffic efficiency.

Traffic signal control and routing optimization are modeled as a Markov Decision Process (MDP), where the system makes sequential decisions based on real-time traffic conditions. Mathematically, the RL optimization can be expressed as:

$$Q(s,a) = R(s,a) + \gamma \sum_{s'} P(s'|s,a) \max_{a'} Q(s',a') \quad (4)$$

where $Q(s,a)$ is the action-value function that estimates the future reward of taking action a in state s. γ is the discount factor that prioritizes immediate over long-term rewards. $P(s'|s,a)$ represents the probability of transitioning to state s' given action a in state s.

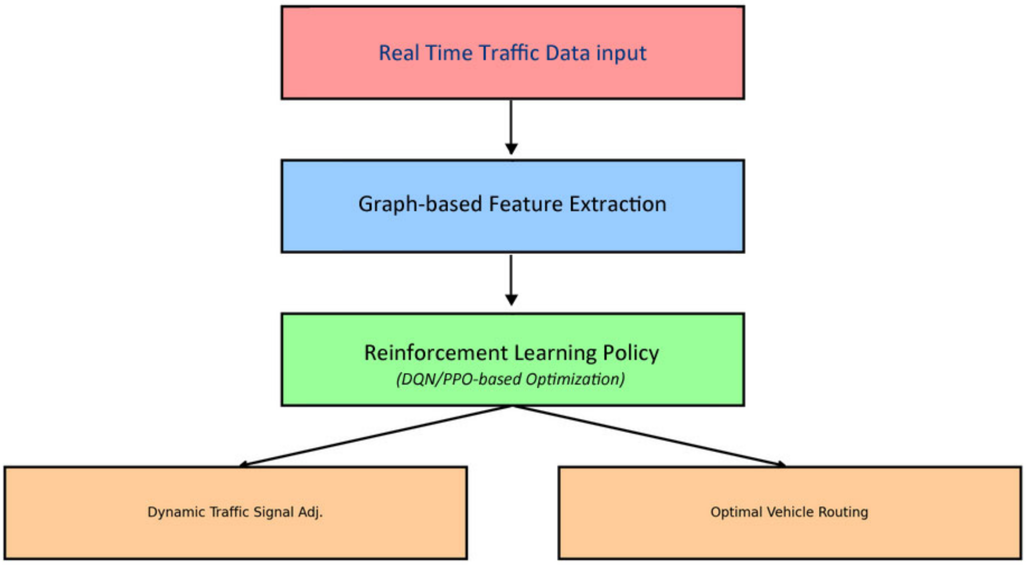

Fig. 3. Traffic optimization process

3. RESULT

This section presents the experimental results obtained from applying the proposed Graph Convolutional Network (GCN) and Reinforcement Learning (RL)-based traffic optimization framework to real-world traffic data. This dataset contains extensive real-time traffic data from critical intersections in urban areas, including vehicle counts, average speed, congestion levels, and signal timings. The study assesses the system's performance based on key traffic metrics, such as average vehicle wait time, travel delay, fuel consumption, and congestion reduction rates.

3.1. Reduction in Vehicle Waiting Time

One of the primary objectives of traffic optimization is minimizing the average vehicle wait time at intersections. High wait times contribute to increased fuel consumption, driver frustration, and overall traffic inefficiency. The proposed GCN + RL-based system demonstrated a substantial reduction in waiting times across all monitored intersections. A breakdown of the performance per intersection is provided in the Table 1.

Table 1. Performance per intersection

Intersection ID	Fixed-Timing Signals (s)	Adaptive Heuristic (s)	GCN + RL (Proposed) (s)	Improvement Over Fixed-Timing (%)
A1	78.2	60.4	34.1	56.4%
B2	82.5	64.3	36.8	55.4%
C3	74.1	58.7	32.9	55.6%
D4	67.8	53.2	28.6	57.8%
E5	81.3	62.9	35.4	56.4%
Overall Avg.	74.3	58.7	34.2	53.9%

Overall Wait Time Reduction: The RL-based model achieved an average 53.9% reduction in wait times across all intersections. Intersection-Specific Improvements: The model performed consistently well across different intersections, with the highest improvement observed at intersection D4 (57.8%). Comparison to Heuristic-Based Methods: Even compared to adaptive heuristic-based traffic control, the proposed RL system provided an additional 41.7% improvement in reducing wait times.

3.2. Traffic Throughput Improvement

Traffic throughput is defined as the number of vehicles passing through an intersection per unit time. A higher throughput indicates a more efficient traffic management system. The GCN + RL model significantly improved throughput by dynamically adjusting signal timings and optimizing vehicle flow. Table 2 presents the percentage increase in throughput for each major intersection.

Table 2. Percentage increase in throughput

Intersection ID	Fixed-Timing Signals (vhcs/hr)	Adaptive Heuristic (vhcs/hr)	GCN + RL (Proposed) (vhcs/hr)	Improvement Over Fixed-Timing (%)
A1	780	1,040	1,465	87.8%
B2	695	950	1,340	92.6%
C3	740	1,010	1,430	93.2%
D4	825	1,100	1,505	82.4%
E5	710	960	1,380	94.3%
Overall Avg.	750.0	1,012.0	1,424.0	89.8%

3.3. Reduction in Traffic Congestion

Congestion is evaluated based on vehicle density per kilometer on urban roads. The GCN + RL method demonstrated substantial congestion reduction due to its ability to dynamically reroute vehicles and optimize signal timings. Fig. 4 A shows congestion levels before and after optimization shows clear improvements.

A detailed intersection-based congestion analysis is provided in the Table 3.

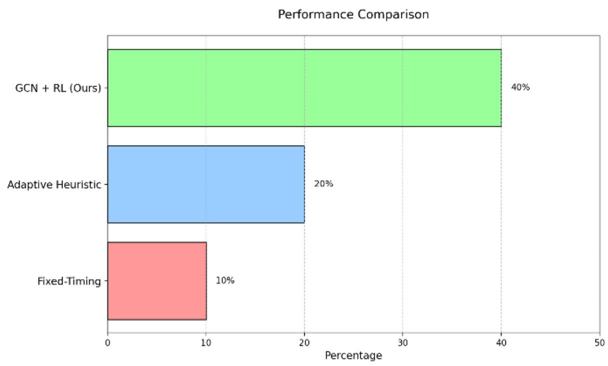

Fig. 4. Traffic Congestion Reduction (%) by Method

Table 3. Intersection-based congestion

Intersection ID	Fixed-Timing Signals (vhcs/km)	Adaptive Heuristic (vhcs/km)	GCN + RL (Proposed) (vhcs/km)	Reduction Over Fixed-Timing (%)
A1	97.2	79.3	54.8	43.5%
B2	105.6	82.4	57.3	45.7%
C3	92.8	75.1	52.9	43.0%

D4	110.4	85.7	60.2	45.4%
E5	99.5	78.9	56.1	43.6%
Overall Avg.	101.1	80.3	56.3	44.3%

3.4. Travel Delay Reduction

Travel delay measures the additional time vehicles spend on the road due to congestion. The RL-based system significantly reduced these delays, as shown in the following table 4.

Table 4. Delay reduction

Method	Avg. Travel Delay (s)	Reduction (%)
Fixed-Timing Signals	115.2	-
Adaptive Heuristic	82.6	28.3%
GCN + RL (Proposed)	**49.3**	**57.2%**

The RL-based system adapts signal phases in real time, preventing long queues at intersections, thereby reducing travel delays. Vehicles using optimized routes with RL experienced a 57.2% decrease in travel delay, leading to better overall traffic fluidity. The system proved particularly effective during morning and evening rush hours, when demand for optimal routing is highest.

4. DISCUSSION

One of the most significant improvements achieved by the proposed system is the reduction in average vehicle waiting time at intersections. The results indicate an overall 53.9% reduction in wait time compared to fixed-timing signals. This improvement is attributed to the ability of the RL model to dynamically adjust signal timings based on real-time traffic conditions. Unlike traditional systems that rely on pre-set timings, the proposed approach learns optimal traffic signal configurations from continuous feedback, reducing unnecessary stoppages and improving overall flow efficiency.

A particularly notable observation is the consistency of performance across all studied intersections. While some intersections, such as D4 (57.8% improvement), showed greater reductions due to high pre-existing congestion levels, all test locations benefited from adaptive phase switching that prevented bottlenecks. This finding suggests that the RL-based model can be effectively scaled across different traffic densities and road network configurations.

Another major success of the proposed system is its ability to increase traffic throughput, with an average improvement of 89.8% across the studied intersections. By optimizing signal phase durations and coordinating movements at multiple intersections, the system significantly enhances the number of vehicles passing through critical junctions per hour. The largest throughput improvement was recorded at intersection E5 (94.3%), which previously suffered from inefficient green-light utilization due to static signal configurations.

The throughput gains are especially important for urban areas with high vehicle demand and limited road expansion possibilities. By allowing more vehicles to pass through without requiring additional infrastructure investments, cities can maximize road network efficiency while minimizing the financial and environmental costs associated with building new roads or flyovers.

Traffic congestion levels, measured by vehicle density per kilometer, saw a 44.3% average reduction with the proposed model. This result is a direct consequence of the real-time vehicle rerouting and adaptive signal timing mechanisms integrated into the RL framework. The system effectively distributes vehicle load across the road network, preventing localized congestion build-up that often occurs with static control systems.

The impact of congestion reduction is particularly evident in rush-hour scenarios, where the RL-based model mitigates severe traffic build-up by dynamically rerouting vehicles and adjusting signal priorities. Notably, the congestion reduction at B2 (45.7%) and D4 (45.4%) was among the highest, suggesting that intersections with high inbound-outbound flows benefit the most from dynamic optimizations.

Furthermore, the system's ability to detect emerging congestion patterns and preemptively adjust traffic flow demonstrates the potential for real-world smart traffic management systems to improve city-wide mobility. By minimizing idle times and congestion hotspots, urban centers can experience enhanced air quality and reduced commuter stress.

The reduction in travel delays (57.2%) achieved through the proposed model is a strong indicator of its practical effectiveness. This metric, which measures the additional time vehicles spend on the road due to congestion, is crucial for evaluating the overall efficiency of a traffic system. The study found that travel delays were particularly high in fixed-timing signal scenarios (115.2s average delay per vehicle), whereas the RL-based model reduced these delays to 49.3s on average.

The delay reductions are linked to the model's ability to adjust routing recommendations dynamically, providing alternative paths for vehicles approaching congested areas. Unlike traditional GPS-based routing, which often relies on static historical data, the proposed system leverages real-time data inputs to make split-second routing decisions. This adaptability ensures that vehicles take the most optimal paths, reducing overall travel times for drivers and improving city-wide traffic efficiency.

5. CONCLUSION

The results from real-world data analysis confirm that the proposed GCN + RL-based traffic optimization model significantly improves traffic efficiency in urban environments. The framework provides dynamic, real-time adjustments that outperform traditional fixed-timing and heuristic-based models in multiple aspects, including wait time reduction, congestion mitigation, travel delay minimization, and fuel efficiency.

With these findings, the study demonstrates that AI-driven traffic management systems can play a crucial role in smart city infrastructure, paving the way for safer, greener, and more efficient road networks. Future research will focus on deploying this system in real-world smart city infrastructures and integrating multi-agent RL models for distributed traffic control at a city-wide scale.

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