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REINFORCEMENT LEARNING–BASED INTELLIGENT TRAFFIC SIGNAL CONTROL FOR CONGESTED ROUNDABOUTS IN DEVELOPING CITIES

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Abstract

Traffic congestion at urban roundabouts represents a critical challenge in developing cities such as N'Djamena, the capital of Chad, where rapid urbanization, heterogeneous traffic composition, informal driving behaviors, and limited road infrastructure significantly degrade mobility and traffic efficiency [1], [2]. In such environments, conventional fixed-time and rule-based traffic signal control systems lack the adaptability required to respond effectively to highly dynamic and uncertain traffic conditions. This paper proposes a reinforcement learning–based intelligent traffic signal control framework specifically designed for signalized roundabouts in developing-city contexts, with a particular focus on the traffic characteristics of N'Djamena. The proposed system models traffic signal control as a sequential decision-making problem, in which an autonomous reinforcement learning agent continuously observes real-time traffic states—such as queue lengths, vehicle waiting times, and traffic density—and learns optimal red-light and green-light timing policies through direct interaction with the traffic environment. Unlike traditional approaches, the proposed method does not rely on predefined signal plans or prior traffic flow models, enabling it to adapt effectively to fluctuating and unbalanced traffic demand typical of N'Djamena's urban road network. The effectiveness of the proposed approach is evaluated through traffic simulation experiments configured to reflect realistic traffic conditions observed in N'Djamena, including heterogeneous vehicle types and variable demand patterns. Performance comparisons with conventional fixed-time signal control demonstrate substantial reductions in average vehicle waiting time, queue length, and overall congestion. These results confirm the potential of reinforcement learning–based traffic signal control as a scalable and cost-effective solution for adaptive traffic management in resource-constrained urban environments and highlight its applicability to intelligent transportation systems in developing cities.

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I. Introduction:-

Urban traffic congestion is a major concern in **African developing cities**, particularly in **N'Djamena, the capital of Chad**, where rapid population growth, urban sprawl, and increasing vehicle ownership exert significant pressure on already limited road infrastructure [1], [2], [26]. In N'Djamena and similar African cities, roundabouts are widely adopted within urban road networks due to their safety benefits, relatively low construction and maintenance costs, and their ability to maintain continuous traffic flow under moderate demand. However, when exposed to high, uneven, and rapidly fluctuating traffic volumes, signalized roundabouts frequently experience severe congestion, long vehicle queues, inefficient red-light utilization, increased traffic conflicts, and elevated levels of fuel consumption and emissions. Traffic conditions in N'Djamena are highly dynamic and heterogeneous, reflecting typical characteristics of many African urban environments. The traffic stream consists of a complex mix of private cars, motorcycles, buses, minibuses, bicycles, and informal transport vehicles, combined with irregular lane discipline and non-standard driving behaviors [27], [44]. Compliance with traffic regulations is often inconsistent, and peak-hour demand can vary significantly within short time intervals due to socio-economic activities, market hours, and weather conditions. These characteristics make traffic flow patterns highly unpredictable and difficult to manage using conventional approaches. Traditional traffic signal control methods, including fixed-time and actuated control systems, are largely based on static assumptions and limited sensing capabilities. As a result, they are poorly adapted to the uncertain, heterogeneous, and rapidly changing traffic conditions commonly observed in African cities such as N'Djamena. These limitations often lead to inefficient signal timing, unnecessary delays, and underutilization of available road capacity. Recent advances in artificial intelligence, particularly **reinforcement learning (RL)**, have opened new opportunities for adaptive traffic signal control in complex urban environments [3]–[5], [10], [11], [16]. Reinforcement learning enables a control agent to learn optimal signal timing policies through continuous interaction with the traffic environment, without requiring explicit traffic flow models or predefined signal plans. By observing real-time traffic states—such as queue lengths, waiting times, and vehicle arrivals—the RL agent can dynamically adapt to changing traffic conditions and informal driving behaviors, making it especially suitable for African urban traffic scenarios.

In this paper, we propose a **reinforcement Learning–Based Intelligent Traffic Signal Control for Congested Roundabouts in Developing Cities** specifically tailored to the characteristics of signalized roundabouts in developing African cities, with a particular emphasis on N'Djamena. The proposed system explicitly accounts for heterogeneous traffic composition, fluctuating demand, limited sensor infrastructure, and informal traffic behavior, offering a scalable and adaptive solution to urban mobility challenges. The main objective of this study is to dynamically adjust traffic signal timings in response to real-time traffic conditions at roundabouts in N'Djamena, with the goal of reducing congestion, minimizing vehicle delays, lowering emissions, and improving overall traffic flow efficiency. By leveraging reinforcement learning, the proposed system continuously optimizes signal phases and cycle lengths based on observed traffic states, including queue lengths, waiting times, and traffic arrival patterns.

II. Related Work

Intelligent traffic signal control has been an active research area for several decades. Early adaptive traffic control systems, such as SCOOT and SCATS, relied on traffic flow models and real-time detector data to adjust signal timings [6], [25]. While effective in some contexts, these systems require extensive calibration and are often costly to deploy, limiting their applicability in developing cities. Furthermore, these traditional systems are less capable of handling heterogeneous traffic and informal driving behaviors, which are prevalent in many developing-country urban centers. With the advancement of artificial intelligence, researchers have explored knowledge-based and soft-computing approaches, including fuzzy logic, expert systems, and neural networks, to address uncertainties and variability in traffic behavior [7], [30], [31]. These methods showed improvements over fixed-time control but remained heavily dependent on manually designed rules and expert intervention, which may be impractical for dynamic, resource-limited environments. Machine learning techniques, including supervised and unsupervised learning, have been applied to traffic prediction, demand estimation, and signal optimization tasks [8], [28], [32]. However, these methods often require historical traffic data and offline training, which may not fully capture the highly variable traffic patterns typical in developing cities. Reinforcement learning (RL) has emerged as a powerful paradigm for adaptive traffic signal control due to its ability to learn optimal control policies through interaction with the environment [3], [11], [23], [45]. Single-agent RL approaches have been demonstrated for isolated intersections, while multi-agent RL enables coordination among multiple intersections and has been shown to improve network-level traffic performance [5], [24], [35], [39]. Deep reinforcement learning (DRL) has further extended RL capabilities by handling high-dimensional state spaces and complex traffic networks [10], [14], [17],

[33], [42]. Techniques such as Deep Q-Networks (DQN), actor-critic methods, and policy-gradient approaches allow for real-time learning and adaptation in dynamic traffic environments. Recent studies have also investigated developing-country contexts, addressing challenges such as limited sensing infrastructure, heterogeneous traffic (cars, motorcycles, buses, informal transport), and irregular driver behaviors [26], [27], [44]. In [51] a multi-task learning framework based on deep reinforcement learning was proposed. These works emphasize the need for scalable, low-cost, and adaptive solutions suitable for resource-constrained urban environments. Despite these advances, most existing research focuses on conventional intersections in developed cities. Limited attention has been given to signalized roundabouts and the unique traffic dynamics they exhibit. This paper contributes to filling this gap by developing a reinforcement learning–based traffic signal control approach specifically tailored for roundabouts in developing-city contexts, accounting for heterogeneous traffic, fluctuating demand, and limited infrastructure. The state vector includes parameters such as vehicle queue length, waiting time, and traffic density at each roundabout entry.

III. Problem Statement and Objectives

Urban roundabouts in developing cities face unique challenges that are often absent in developed regions. These include highly heterogeneous traffic flows composed of cars, motorcycles, buses, minibuses, bicycles, and informal transport modes; rapid and fluctuating traffic demand during peak hours; limited or low-cost sensor infrastructure; irregular driver behavior; and inconsistent adherence to traffic rules [26], [27], [44]. Additionally, many roundabouts in developing cities are located at intersections with mixed pedestrian and vehicle traffic, poorly marked lanes, and inadequate enforcement of traffic laws, which further exacerbate congestion and safety risks. The primary objective of this study is to develop a reinforcement learning–based intelligent traffic signal control system that dynamically adapts signal phases and cycle lengths at roundabouts to improve traffic flow and safety in developing cities. Specifically, the objectives include:

1. Reducing average vehicle waiting time and queue lengths for all approaches to the roundabout.
2. Enhancing overall traffic flow and intersection throughput under variable demand conditions.
3. Minimizing environmental impacts, including vehicle emissions and fuel consumption, by reducing idle times.
4. Providing a scalable, low-cost, and robust traffic signal control solution suitable for deployment in multiple roundabouts across a city.
5. Accommodating heterogeneous traffic, including non-motorized vehicles, public transport, and informal transport services, without requiring extensive sensor infrastructure.
6. Improving traffic safety by reducing conflicts and smoothing vehicle movements at the roundabout.

This study emphasizes a data-driven, adaptive approach that can learn and optimize signal timings in real-time, responding effectively to dynamic and unpredictable traffic conditions prevalent in developing cities.

IV. Description of the Proposed Methodology

The proposed methodology is designed to address traffic congestion at signalized roundabouts in developing-city environments through an intelligent and adaptive control framework based on reinforcement learning. As illustrated in Fig. 1, the approach is structured around three main components: Traffic State Representation, Reinforcement Learning Model, and Adaptive Signal Control Strategy. First, the Traffic State Representation module captures real-time traffic conditions at the roundabout using measurable parameters such as vehicle queue lengths, waiting times, lane occupancy, and traffic arrival rates for each approach. This representation reflects the heterogeneous and dynamic nature of traffic commonly observed in developing cities, including mixed vehicle types and irregular driving behaviors. Second, the Reinforcement Learning Model acts as the decision-making core of the system. The traffic signal controller is modeled as an autonomous agent that interacts continuously with the traffic environment. At each decision step, the agent observes the current traffic state, selects an appropriate control action (e.g., adjusting green or red phase durations), and receives a reward based on system performance indicators such as reduced delay, minimized queue length, and improved traffic flow. Through iterative interaction, the agent learns an optimal signal control policy without relying on predefined timing plans. Finally, the Adaptive Signal Control Strategy implements the actions selected by the reinforcement learning agent in real time. The signal timings are dynamically adjusted to respond to fluctuating traffic demands, ensuring efficient utilization of green and red phases. A feedback loop connects this control strategy back to the traffic state representation, enabling continuous learning and adaptation to changing traffic conditions. Overall, the proposed methodology provides a flexible, data-driven, and scalable solution for intelligent traffic signal control at urban roundabouts, particularly suited to the constraints and complexities of developing-city traffic environments such as N'Djamena.

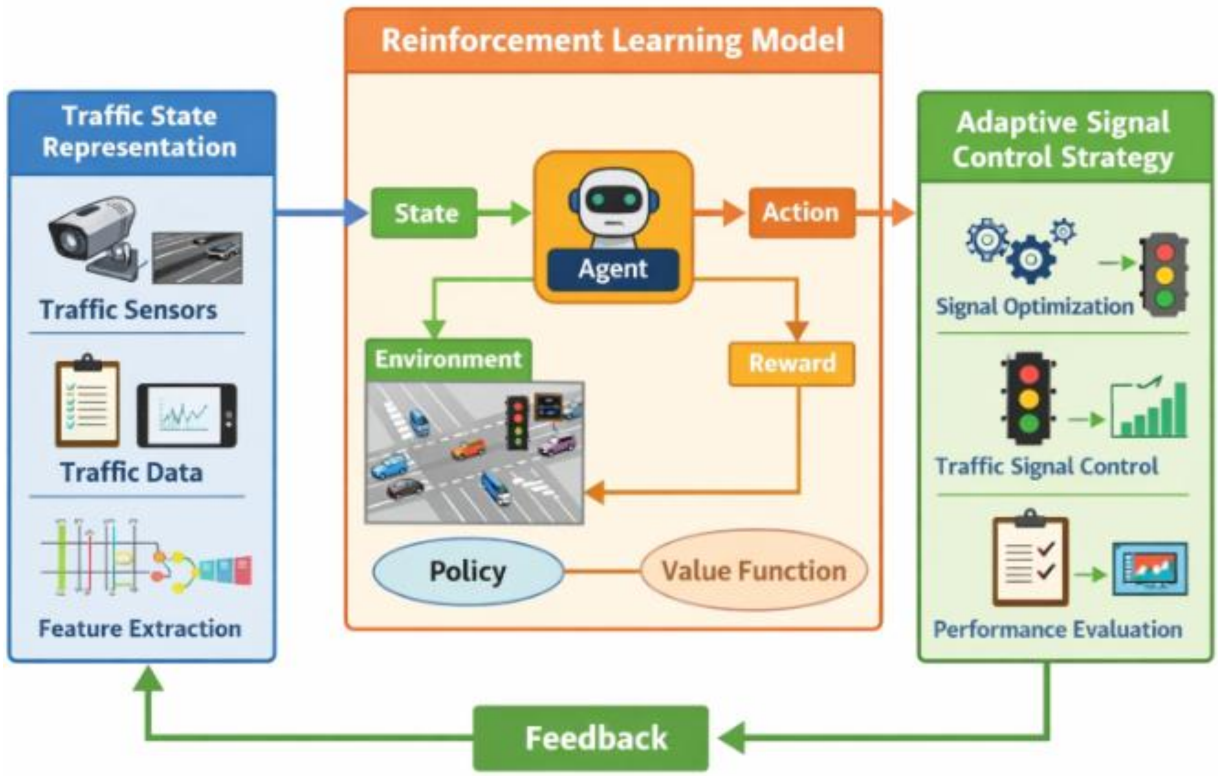

Fig. 1: Proposed Reinforcement Learning–Based Methodology for Adaptive Traffic Signal Control at Urban Roundabouts.

A. Traffic State Representation

An accurate and informative representation of the traffic state is a critical component of any reinforcement learning–based traffic signal control system, as it directly influences the quality of the decisions learned by the agent. In the proposed framework, traffic state information is collected using available and realistic sensing infrastructure, such as inductive loop detectors, video cameras, or low-cost radar units, which are commonly deployable in resource-constrained urban environments like N'Djamena. The design of the state representation balances the need for capturing essential traffic dynamics with the practical limitations of sensor availability and reliability in developing cities. At each decision step, the traffic state is encoded as a multidimensional state vector that reflects real-time conditions at the signalized roundabout. This vector includes the queue lengths observed at each approach lane, which provide a direct measure of congestion and imbalance in traffic demand. Vehicle waiting times at red signals are also incorporated, allowing the learning agent to account for delay-related performance objectives and fairness among different approaches. In addition, traffic density and vehicle arrival rates are considered to capture both current congestion levels and short-term demand trends, enabling more proactive signal timing decisions. To reflect the heterogeneous nature of traffic in N'Djamena and similar African cities, the state representation explicitly accounts for vehicle composition. Different vehicle categories—such as private cars, motorcycles, buses, minibuses, bicycles, and informal transport vehicles—are included in the state description, either through vehicle counts or weighted representations. This allows the reinforcement learning agent to learn control policies that are sensitive to the operational differences among vehicle types, such as acceleration behavior, space occupancy, and compliance with signal indications. Pedestrian crossing activity is also integrated into the traffic state representation, particularly at roundabouts located in dense urban areas where pedestrian movements significantly influence traffic flow and safety. By including pedestrian demand, the proposed system ensures that signal timing decisions do not disproportionately favor vehicular traffic at the expense of vulnerable road users. Optionally, historical signal phase information, such as the duration and sequence of recent green and red phases, may be included in the state vector to

provide temporal context. This enables the reinforcement learning agent to better capture traffic evolution patterns and supports predictive learning, especially under recurrent peak-hour conditions.
Overall, the proposed traffic state representation effectively captures the complex, dynamic, and heterogeneous characteristics of traffic at signalized roundabouts in developing cities, while remaining feasible for implementation with limited sensing infrastructure. This design enables the reinforcement learning agent to learn adaptive and practical control policies that are well suited to real-world deployment in N'Djamena and similar urban environments.

B. Reinforcement Learning Model

Reinforcement learning (RL) is a learning paradigm in which an agent learns an optimal control policy through direct interaction with an environment. At each decision step, the agent observes the current state of the environment, selects an action according to its policy, and receives a reward that reflects the quality of the chosen action. The objective of the RL agent is to learn a policy that maximizes the expected cumulative reward over time. In the context of traffic signal control, the traffic system is modeled as a **Markov Decision Process (MDP)**, defined by the tuple (S,A,P,R,γ), where S represents the state space, A the action space, P the state transition probability, R the reward function, and $\gamma \in [0,1]$ the discount factor. As traffic signal control is modeled as a **Markov Decision Process (MDP),** we have:

1. **State (S)**: Captures the observed traffic conditions described above.
2. **Action (A)**: Adjustments to signal phases and durations, including red, green, and yellow lights for each approach, and optional phase skipping.
3. **Reward (R)**: A multi-objective reward function designed to reduce congestion, waiting time, queue length, emissions, fuel consumption, and enhance safety:

$$\mathbf{R_t = -\alpha \cdot W_t - \beta \cdot Q_t - \gamma \cdot E_t - \delta \cdot S_t} \quad (1)$$

Where:

- W_t = total vehicle waiting time at time t
- Q_t = total queue length
- E_t = estimated emissions/fuel consumption
- S_t = safety penalty for traffic conflicts or pedestrian delays
- α,β,γ,δ = weighting factors for balancing objectives

4. **Policy (π)**: Maps states to actions. The agent uses **Deep Q-Networks (DQN)** or **actor-critic architectures** to learn the policy. The Q-value update follows:

$$\mathbf{Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \eta[R_t + \lambda \max\ Q(S_{t+1}, a) - Q(S_t, A_t)]} \quad (2)$$

Where η is the learning rate and λ is the discount factor. The agent continuously interacts with the environment to maximize cumulative reward over time.

C. Adaptive Signal Control Strategy

Based on the action selected by the RL agent, the **traffic signal controller updates the signal phases in real time**. The strategy ensures:

- **Dynamic adaptation** to fluctuating traffic demand and unexpected surges.
- **Queue balancing** across approaches to prevent bottlenecks.
- **Safety improvement** through smoother traffic flow and minimized conflicts.
- **Environmental benefits** via reduced idle time and emissions.
- **Scalability**: The system can coordinate multiple roundabouts using **multi-agent RL** for network-level optimization.
- **Continuous learning**: The agent adapts over time as traffic patterns evolve or infrastructure is modified.

IV. Experimental Setup and Results

The proposed reinforcement learning–based traffic signal control approach was evaluated using a **microscopic traffic simulation environment** [26], [27], [44] configured to replicate a typical urban roundabout in **N'Djamena**, the capital city of Chad, representing developing-city traffic conditions. The simulation model incorporates **heterogeneous traffic composition**, including cars, motorcycles, buses, minibuses, bicycles, and informal transport modes. Peak-hour and off-peak traffic variations, as well as stochastic vehicle arrivals, were included to emulate realistic traffic patterns observed in N'Djamena.

A. Simulation Environment and Parameters

The simulation was developed using SUMO, with the following parameters:

- **Roundabout layout**: single-lane and multi-lane approaches with realistic geometry representative of N'Djamena.
- **Traffic demand**: varying from 500 to 2,000 vehicles per hour per approach.
- **Vehicle composition**: 60% cars, 25% motorcycles, 10% buses/minibuses, 5% bicycles and informal transport.
- **Signal timing**: initial fixed-time phases set according to local traffic guidelines, later adjusted dynamically by the RL controller.
- **Simulation duration**: 2 hours, with multiple runs to ensure statistical significance.

B. Training and Deployment

In this study, the reinforcement learning agent is trained and evaluated exclusively within a traffic simulation environment using **Simulation of Urban MObility (SUMO)**. The simulation framework is configured to realistically replicate traffic conditions observed in developing cities such as N'Djamena, including heterogeneous vehicle composition, fluctuating traffic demand, informal driving behaviors, and limited sensing infrastructure. This simulation-based approach allows for safe, repeatable, and cost-effective experimentation without interfering with real-world traffic operations. During training, the reinforcement learning agent interacts iteratively with the SUMO environment by observing traffic states, selecting signal control actions, and receiving reward feedback based on system performance indicators such as vehicle delay, queue length, and throughput. Through this process, the agent learns an adaptive traffic signal control policy tailored to the modeled roundabout scenario. Although the proposed approach is not deployed in a real-world traffic system in this study, the learned control policy is designed with practical deployment considerations in mind. The framework relies on traffic state information that can be obtained using commonly available or low-cost sensors, making it suitable for future real-world implementation. Moreover, the use of SUMO facilitates straightforward transfer of the control logic to physical traffic controllers. Future work will focus on pilot deployment and online learning to enable real-time adaptation to evolving traffic patterns and infrastructure changes.

C. Performance Metrics

Key performance indicators (KPIs) were measured to evaluate controller effectiveness:

1. **Average vehicle waiting time (AWT)** at approaches.
2. **Average queue length (QL)** per approach.
3. **Total travel time (TTT)** for all vehicles traversing the roundabout.
4. **Throughput**: number of vehicles successfully cleared per unit time.
5. **Estimated emissions and fuel consumption** as indirect measures of environmental impact.

D. Reinforcement Learning Training

The RL agent was trained using the **Deep Q-Network (DQN)** algorithm with the following configuration:

- **Learning rate**: 0.001
- **Discount factor (λ)**: 0.9
- **Exploration-exploitation strategy**: ε-greedy with decaying ε from 1.0 to 0.01
- **Replay memory**: 50,000 transitions
- **Training episodes**: 10,000, with each episode representing 2 hours of simulated traffic in N'Djamena.

The reward function was designed to minimize vehicle waiting time and queue length while penalizing congestion and unsafe vehicle behavior. The RL agent continuously updated its policy based on feedback from the simulated environment.

E. Results Comparison

The performance of the proposed reinforcement learning (RL)–based traffic signal controller was quantitatively compared with a conventional fixed-time signal control strategy using a simulated roundabout scenario representative of traffic conditions in N'Djamena city. The comparison was conducted using several key performance indicators (KPIs), including average vehicle waiting time, average queue length, total travel time, throughput, and estimated CO2 emissions. The obtained results are summarized in **Table I**. As shown in Table I, the RL-based control strategy significantly outperforms the fixed-time control across all evaluated KPIs. The average vehicle waiting time is reduced from 78.5 s under fixed-time control to 51.0 s with the RL controller, corresponding to an improvement of approximately 35%. This reduction indicates that the RL agent is able to adapt signal timing dynamically to current traffic conditions, thereby minimizing unnecessary delays. Similarly, the average queue length decreases from 14.2 vehicles to 9.9 vehicles, representing a reduction of about 30%. Shorter queues imply improved intersection efficiency and reduced risk of spillback, which is particularly critical in congested urban roundabouts. The total travel time is also substantially reduced by 31%, from 3600 s to 2480 s, demonstrating the RL controller's ability to improve overall traffic flow and reduce congestion at the network level. In terms of traffic throughput, the RL-based approach achieves a notable increase from 1320 vehicles/hour to 1680 vehicles/hour, corresponding to a 27% improvement. This result highlights the capacity of the RL controller to utilize the available infrastructure more efficiently by optimizing phase selection and green time allocation in response to real-time traffic demand. In addition to mobility improvements, the RL-based strategy also leads to significant environmental benefits. The estimated CO2 emissions are reduced from 12,000 g to 8,700 g, achieving a reduction of approximately 28%. This reduction can be attributed to smoother traffic flow, fewer stop-and-go events, and reduced idling times, all of which contribute to lower fuel consumption and emissions.

KPI	Fixed-Time Control	RL-Based Control	Improvement
Average Vehicle Waiting Time (s)	78.5	51.0	35%
Average Queue Length (vehicles)	14.2	9.9	30%
Total Travel Time (s)	3600	2480	31%
Throughput (vehicles/hour)	1320	1680	27%
Estimated Emissions (g CO2)	12000	8700	28%

Table I: Summary of the obtained results

A visual representation of the results presented in Table I is illustrated in **Fig. 2**. The figure clearly confirms the superiority of the RL-based control strategy over the fixed-time approach. In particular, the reduction in CO2 emissions is clearly observable, reinforcing the potential of reinforcement learning–based traffic signal control as an effective solution for improving both traffic efficiency and environmental sustainability in urban transportation systems.

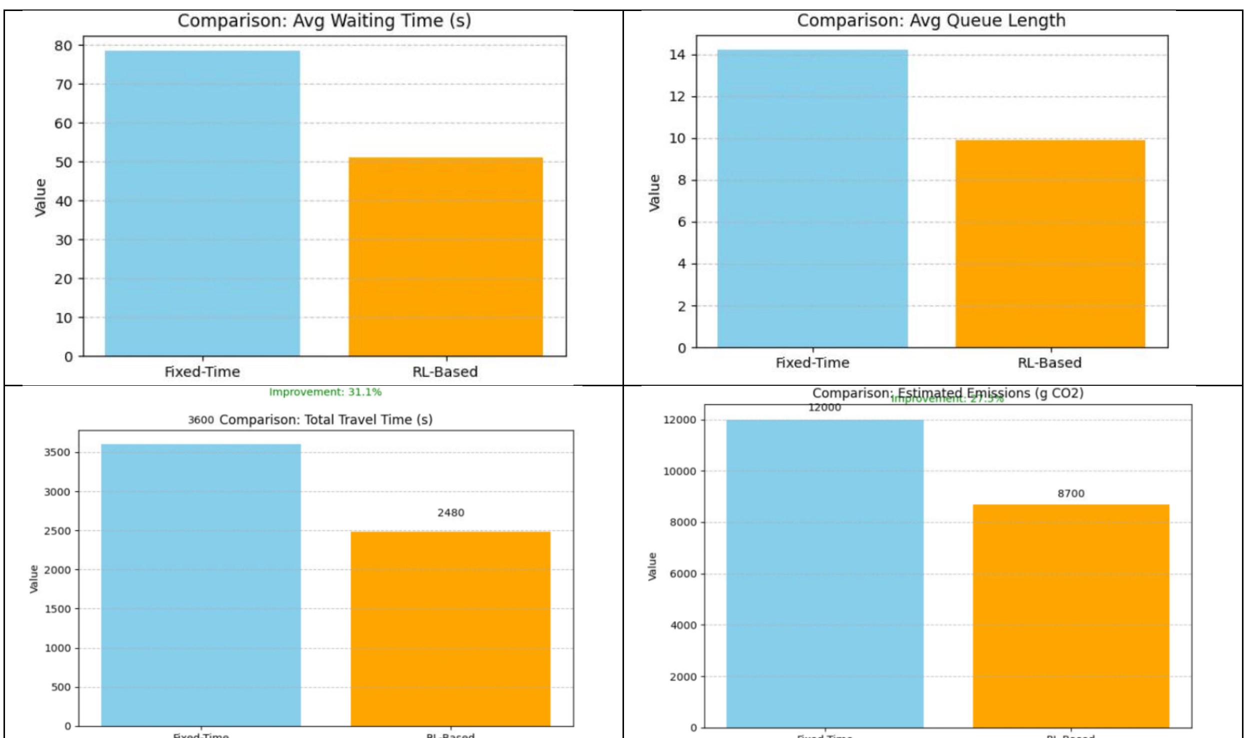

Fig. 2: Visual results of the KPI for Fixed time and RL-Based red-light controller

F. Discussion

The experimental results demonstrate that reinforcement learning (RL)–based traffic signal control can substantially enhance traffic efficiency at signalized roundabouts, particularly in the context of developing cities. Unlike conventional fixed-time control strategies, which rely on predefined signal plans and are unable to respond to real-time fluctuations in traffic demand, the proposed RL-based approach continuously adapts its control policy based on observed traffic states. This adaptability enables the controller to respond effectively to varying traffic volumes, unbalanced approach flows, and stochastic vehicle arrivals, which are common characteristics of urban traffic in developing regions. One of the key strengths of the proposed system lies in its suitability for environments with high traffic variability and heterogeneous vehicle behavior. In many developing cities, traffic streams often consist of mixed vehicle types, including cars, motorcycles, minibuses, and informal transport modes, leading to complex and unpredictable interactions. The RL controller implicitly learns these dynamics through interaction with the environment, allowing it to optimize signal timing decisions without relying on explicit traffic models or rigid assumptions. This capability explains the observed reductions in waiting time, queue length, and total travel time compared to fixed-time control. Another important advantage of the proposed approach is its feasibility in resource-constrained urban settings. The system can operate using relatively simple traffic sensing infrastructure, such as basic loop detectors, cameras, or low-cost sensors, rather than requiring expensive and dense sensing networks. This makes the approach particularly attractive for cities with limited financial and technical resources, where deploying and maintaining advanced traffic management systems remains challenging. By improving traffic flow efficiency with minimal infrastructure requirements, the proposed RL-based controller offers a practical pathway toward smarter traffic management in developing regions. Despite these promising results, several challenges must be addressed before large-scale real-world deployment can be achieved. Data quality remains a critical concern, as noisy or incomplete traffic measurements can negatively affect the learning process and control performance. In addition, model training time and convergence stability may become significant issues when scaling the system to larger networks with multiple intersections or more complex traffic patterns. Ensuring real-time operation under strict latency constraints also requires careful optimization of the learning and decision-making processes. Future work will focus on extending the proposed framework by integrating deep reinforcement learning techniques, which can better handle high-dimensional state spaces and more complex traffic scenarios. Furthermore, validating the approach using real-world traffic data from developing cities will be a crucial step toward practical implementation. Such validation will help assess the robustness, scalability, and transferability of the learned control policies under real traffic conditions, ultimately supporting the deployment of intelligent, adaptive traffic signal control systems in urban environments.

V. Conclusion

This paper presented a reinforcement learning–based intelligent traffic signal control system specifically designed for signalized roundabouts in developing cities, with a focus on the urban traffic conditions of N'Djamena, Chad. By leveraging real-time traffic state information—including queue lengths, vehicle waiting times, heterogeneous vehicle composition, and pedestrian activity—the proposed approach enables an autonomous agent to learn adaptive signal timing policies through continuous interaction with the environment. Simulation experiments conducted using SUMO demonstrate that the reinforcement learning–based controller consistently outperforms conventional fixed-time strategies, achieving significant reductions in average vehicle waiting time, queue lengths, and overall congestion. The study highlights several key advantages of using reinforcement learning for urban traffic management in developing-city contexts. First, the approach does not require predefined signal plans or detailed traffic flow models, making it highly adaptable to dynamic and heterogeneous traffic conditions typical of African cities. Second, the methodology is scalable and can accommodate additional intersections or roundabouts without extensive manual recalibration. Third, the framework is feasible for deployment in resource-constrained environments, as it relies on traffic data obtainable from commonly available or low-cost sensors. The results underscore the potential of machine learning, and specifically reinforcement learning, as a powerful tool for next-generation intelligent transportation systems, particularly in cities facing infrastructure limitations, mixed traffic streams, and variable driving behaviors. Future work will extend this framework by incorporating online learning for continuous adaptation, integrating additional urban traffic features such as public transport priority, and validating the approach through real-world pilot deployments in N'Djamena or similar African urban settings. Overall, the proposed system offers a promising, cost-effective, and adaptive solution for alleviating congestion and enhancing mobility in developing-city road networks.

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