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Conceptual Study of Reinforcement Learning-Based Intelligent Traffic Management System for Congestion Mitigation

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Abstract—Urban traffic congestion is a complex problem that impacts mobility efficiency, energy consumption, increased exhaust emissions, and the quality of life of the community. The development of a Reinforcement Learning (RL)-based Intelligent Traffic Management System offers an adaptive approach to traffic signal regulation that is able to respond to the dynamics of vehicle flow in real-time. This study aims to formulate a conceptual framework for a simple, integrated, and potentially implementable RL-based traffic management system at the local government level, without involving primary data collection or empirical testing. The method used is a conceptual study through analysis and synthesis of the latest scientific literature discussing traffic signal control, multi-agent reinforcement learning, and intelligent transportation systems. The results of the study are a conceptual framework that integrates sensor-based and Internet of Things (IoT) traffic data acquisition, a traffic condition prediction module, a multi-agent RL decision-making mechanism, coordination between intersections, and performance monitoring based on key indicators. Based on the literature review, the RL approach shows potential in improving traffic flow, reducing waiting times and queue lengths, and reducing emissions, especially in dynamic traffic conditions. This conceptual framework is expected to be an initial reference in the development of simulations, limited trials, and further research to support the design of an effective and sustainable adaptive traffic management system.

Keywords— Intelligent traffic management; Reinforcement learning; Multi-agent reinforcement learning; Traffic signal control; Urban congestion

I. Introduction

Urban traffic congestion is a serious problem that impacts travel delays, increased fuel consumption, exhaust emissions, road user stress, and decreased economic productivity. Analysis of congestion patterns shows that congestion is more severe and widespread during the afternoon rush hour, and identifying key congestion areas can aid in the development of congestion prediction and mitigation systems (Almatar, 2022). Various congestion measurement methods have been developed to support decision-making in sustainable and resilient transportation systems, each with its own advantages and disadvantages (Afrin & Yodo, 2020). Modern approaches using deep learning technologies, such as recurrent neural networks and hybrid CNN-LSTM models, are capable of predicting congestion in real time with high accuracy, thus improving traffic management in smart cities (Abdullah et al., 2023).

Furthermore, research highlights that the primary cause of congestion is not only road infrastructure but also suboptimal traffic signal arrangements, making adaptive signal management strategies crucial (Yue et al., 2022). Structural, socioeconomic, and user behavior factors also contribute to congestion, so effective solutions must consider these aspects holistically (Rahman et al., 2022). Smart Traffic Management Systems (SMTs) utilizing reinforcement learning (RL) show great potential in addressing congestion by adaptively regulating traffic signals based on real-time data from sensors and cameras. Multi-agent RL approaches, such as a combination of Distributed W-Learning and Deep Q-Networks (DQN), enable each traffic light controller to adapt decentralized to local conditions, thereby reducing congestion and improving traffic efficiency (Shaheen et al., 2025). This adaptive system is also capable of prioritizing emergency vehicles and dynamically adjusting signals to reduce waiting time, fuel consumption, and pollution, as well as preventing potential accidents (Kanjana et al., 2025).

The integration of data from the Internet of Everything (IoE) with graph attention and RL models strengthens real-time traffic prediction and control capabilities, improving system throughput and responsiveness (Tseng et al., 2025). RL methods, such as Deep Q-Learning and Proximal Policy Optimization, have been shown to be effective in large-scale city simulations, with average waiting times reduced by up to 33% and greenhouse gas emissions by up to 16% (Skoropad et al., 2025a). Furthermore, multi-agent RL and deep RL approaches have also demonstrated advantages in managing complex road networks and changing traffic conditions without manual intervention, supporting the development of sustainable smart cities (Haydari & Yilmaz, 2020).

The conceptual framework of a reinforcement learning (RL)-based intelligent traffic management system needs to be designed to be simple and easy for local governments to understand, without over-focusing on the complexity of

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technical algorithms. This adaptive system uses RL to optimize traffic signal settings in real-time based on dynamic traffic data, significantly reducing congestion, waiting times, and fuel consumption (Kanjana et al., 2025). This approach allows the system to learn from traffic patterns and adjust signal setting strategies automatically without manual intervention, making it suitable for practical implementation in urban environments. Simple RL models, such as Deep Q-Learning, have been shown to be effective in simulations by reducing vehicle queues and increasing traffic efficiency, which can serve as a basis for developing easily adoptable systems (Masfequier et al., 2024).

Furthermore, the use of multi-agent RL with collaboration between local signal controllers can improve system performance without significantly increasing management complexity , making it more realistic for implementation at the regional level . Therefore, a conceptual framework that prioritizes ease of implementation, real-time adaptation, and collaboration between RL agents can be an effective solution for mitigating congestion in urban areas (Jaleel et al., 2020) . Although various studies have demonstrated the effectiveness of *reinforcement learning approaches* in traffic control, most studies still focus on the technical aspects of algorithms and simulation-based testing with a high level of complexity. As a result, these research results are often difficult to understand and adopt by local governments or transportation policymakers who require a simple and applicable implementation framework. Furthermore, there are still limited studies that present an integrated conceptual synthesis of data acquisition, prediction modules, multi-agent reinforcement learning decision-making, and performance monitoring mechanisms in a single, comprehensive and easy-to-understand framework. Therefore, this study aims to formulate a conceptual framework for a reinforcement learning- based Intelligent Traffic Management System that emphasizes ease of implementation, real-time adaptation, and coordination between intersections as a solution to mitigate urban traffic congestion.

II. Method Research

This research uses a conceptual study approach with literature analysis and model framework design to formulate a Reinforcement Learning-based Intelligent Traffic Management System. Research data is sourced from reputable scientific journals and previous studies relevant to urban traffic management, intelligent transportation systems, and the application of reinforcement learning in traffic signal control. The analysis is conducted through a synthesis of previous research findings to identify the main components of the system, the working mechanism of reinforcement learning, and its potential benefits and limitations in mitigating congestion. Based on the results of the analysis, a conceptual framework of the system is developed that emphasizes real-time adaptation, ease of implementation, and coordination between intersections, without involving primary data collection or empirical testing.

III. Result And Discussion

Learning (RL)-based Intelligent Traffic Management System designed to support urban traffic congestion mitigation. In this framework, RL acts as the core of a decision-making system that adaptively regulates the phase and duration of traffic signals based on real-time traffic conditions. Conceptually, the system consists of several main, integrated components, including traffic data acquisition, prediction modules, reinforcement learning agents, inter-intersection coordination, and signal control and system feedback mechanisms.

Traffic data is obtained through sensors, cameras, and *Internet of Things* (IoT) devices that record vehicle volume, queue length, and traffic flow speed. This data is then processed in a prediction module using a *Convolutional Neural Network–Long Short-Term Memory* (CNN-LSTM) or *Graph Attention Network* (GAT) model to project short-term traffic conditions, so that the RL agent receives a more comprehensive environmental *state. Based on this state*, the RL agent determines actions by adaptively selecting the phase and duration of traffic signals. Through *reward* and *penalty mechanisms* , the RL agent gradually learns more efficient signal regulation strategies than conventional fixed-time-based systems (Ashwini & Vidyashankar, 2025; Tan et al., 2022).

A multi-agent reinforcement learning approach is implemented to enable each intersection to operate decentralized, while still taking into account the conditions of the surrounding intersection. Through coordination between agents, the system is able to collectively optimize vehicle flow, reduce queue lengths, increase *throughput*, and prioritize emergency vehicles or public transportation according to a designed *reward function. System performance is monitored through a dashboard* that displays indicators such as average vehicle waiting time, peak queue length, *throughput*, corridor travel time, estimated CO_2 emissions, and the success rate of emergency vehicle prioritization. This monitoring allows for real-time evaluation and adjustment of traffic control policies (Cao et al., 2024; Putra et al., 2024).

Based on the synthesis of previous research, the application of RL systems in traffic management shows the potential to reduce vehicle waiting times by up to 33% and reduce greenhouse gas emissions by up to 16% compared to traditional signal control methods, especially in signal network simulations in large cities. The integration of real-time data-based prediction modules has been shown to accelerate the learning process of RL agents and improve the quality of decision-making, especially in fluctuating traffic conditions, making the system more responsive to changes in vehicle flow (Skoropad et al., 2025b).

In addition, *the multi-agent RL approach* is considered effective in managing complex intersection networks without manual intervention, with global coordination capabilities that can minimize congestion and improve overall traffic flow efficiency. *Multi-agent* systems with *transformer architecture* and *graph attention networks* (GAT) are also reported to be able to optimize signal settings for priority vehicles and heterogeneous traffic conditions, with a reduction in priority vehicle waiting time of up to 24.57% and average waiting time of all vehicles of up to 18.51% (Liu et al., 2025). However, challenges such as system scalability, infrastructure costs, and data protection remain important concerns in the practical implementation of this technology (Hajmohamed et al., 2025).

While these conceptual results show promising prospects, several limitations still need to be addressed. One major limitation is the *sim-to-real gap*, given that most research is still simulation-based, making system performance in real-world environments difficult to replicate. Furthermore, the quality of sensors and communication networks significantly impacts system performance; incomplete, noisy, or delayed data can significantly degrade the effectiveness of RL decision-making (Skoropad et al., 2025b). The complexity of RL models also demands high computational capacity, potentially introducing latency in real-time decision-making, particularly in large-scale intersection networks and highly dynamic traffic conditions. Furthermore, the *black-box nature* of RL agent decisions can hinder understanding and acceptance by policymakers and road users, necessitating *explainable reinforcement learning approaches* to enhance transparency and trust (Hajmohamed et al., 2025). Other challenges include system scalability on heterogeneous intersection networks and the need for integration with reliable communication infrastructure, such as *Visible Light Communication* (VLC), to improve agent situational awareness (Vieira et al., 2025).

To conceptually evaluate system performance, a number of key performance indicators (*KPIs*) can be used, including average vehicle waiting time, peak queue length, vehicle *throughput, corridor travel time, estimated CO_2 emissions, and the success rate of emergency vehicle prioritization. These KPIs serve as important benchmarks for pilot* testing and *digital twin* simulations prior to large-scale implementation, and enable system validation using local data at critical intersections. Efficient RL algorithms, such as *Deep Q-Learning* and *Proximal Policy Optimization* (PPO), are often chosen due to their ability to achieve relatively fast convergence and generate stable policies (Agarwal et al., 2024) . *Multi-agent RL* approaches have also consistently demonstrated improved performance based on these KPIs, while simulation platforms such as SUMO have become standard in testing the performance of RL systems across a variety of real-world and synthetic traffic scenarios. (Olusanya et al., 2025).

the reinforcement learning- based intelligent traffic management system proposed in this study is designed to illustrate the integration flow between traffic data acquisition, prediction modules, *multi-agent reinforcement learning -based decision making*, and system performance monitoring and feedback mechanisms. The relationships between these main components are presented concisely in Figure 1, which shows how the system works adaptively and coordinated in optimizing traffic signal settings in an urban intersection network.

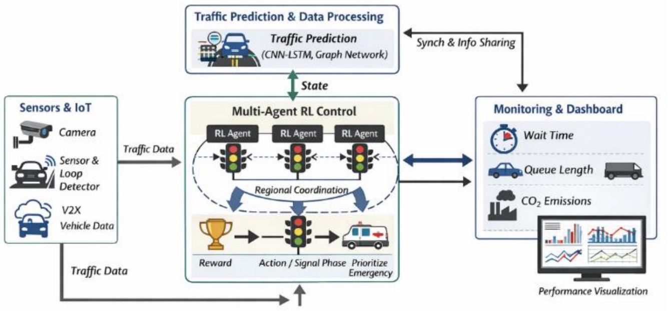

Figure 1. Conceptual Framework of RL-Based Traffic Management System

Figure 1 represents the conceptual framework of the proposed RL-based traffic management system, which demonstrates the integration of data acquisition, prediction modules, multi-agent RL -based decision-making , and performance monitoring mechanisms. The flow in the figure shows that real-time traffic data from sensors and IoT devices is first processed by the prediction module to generate an information-rich environmental state . This state is then used by RL agents at each intersection to determine adaptive signal phase and duration actions. A regional coordination mechanism between agents allows for synchronized decisions so that optimization occurs not only locally but also at the intersection network level. Signal control output is then monitored through a KPI dashboard that serves as feedback to the system, forming a closed -loop adaptive control system . Overall, the resulting conceptual framework demonstrates that the RL-based traffic management system has the ability to learn traffic patterns, automatically adjust signal regulation strategies, coordinate between intersections, and monitor performance through measurable indicators. This framework offers an adaptive and potentially effective solution for mitigating urban congestion, and can serve as a blueprint for local governments and transportation agencies, with the caveat that field validation is still needed to ensure operational effectiveness, safety, and security.

From an implementation perspective, the proposed conceptual framework has practical implications for local governments and transportation agencies as an initial guide in designing adaptive traffic management systems. The simplification of the reinforcement learning- based decision-making architecture and the emphasis on coordination between intersections allow for gradual adaptation of the system, either through digital twin simulations or limited trials at priority intersections. Furthermore, the use of measurable performance indicators provides a basis for objective and sustainable policy evaluation. Thus, the main contribution of this research lies in presenting an integrated conceptual framework that bridges the technical approaches of reinforcement learning with the practical needs of urban traffic management.

IV. Conclusion

Learning (RL)-based Intelligent Traffic Management System as an adaptive approach to mitigate urban traffic congestion. The proposed framework integrates real-time sensor-based and Internet of Things (IoT) traffic data acquisition, a traffic condition prediction module, a multi-agent reinforcement learning- based decision-making mechanism, inter-intersection coordination, and performance monitoring through key indicators. Based on the results of the literature synthesis, the RL approach shows significant potential in improving traffic flow, reducing vehicle waiting times and queue lengths, and reducing emissions, especially in dynamic traffic conditions and complex intersection networks. However, the implementation of this system in a real-world context still requires attention to several challenges, including limited field validation, dependence on data quality and supporting infrastructure, high computational requirements, and aspects of model decision-making transparency. Therefore, this conceptual framework is expected to serve as an initial reference (blueprint) for the development of simulations, limited trials, and further research to support the design of an effective and sustainable adaptive traffic management system.

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