Smart Signal Control Using Reinforcement Learning to Ease Urban Traffic

Sivakumar Ponnusamy[1], M. L. M. Prasad[2], G. Swarnalakshmi[3], S. Karthikeyan[4], S. K. Lokesh Naik[5] and Moses Raja A.[6]

[1]*Department of Computer Science and Engineering, K.S.R. College of Engineering, Tiruchengode, Namakkal, Tamil Nadu, India*

[2]*Department of CSE (AI&ML), Joginpally BR Engineering College, Moinabad, Hyderabad, Telangana, India*

[3]*Department of Mechanical Engineering, New Prince Shri Bhavani College of Engineering and Technology, Chennai, Tamil Nadu, India*

[4]*Department of Electrical and Electronics Engineering, J.J. College of Engineering and Technology, Tiruchirappalli, Tamil Nadu, India*

[5]*Department of Computer Science and Engineering, MLR Institute of Technology, Hyderabad, Telangana, India*

[6]*Department of MCA, New Prince Shri Bhavani College of Engineering and Technology, Chennai, Tamil Nadu, India*

Keywords: Reinforcement Learning, Adaptive Traffic Signals, Urban Congestion, Multi-Agent Systems, Vehicle Flow.

Abstract: This study offers an innovative proposal for the management urban traffic through the implementation of reinforcement learning for adaptive traffic signal systems to overcome the traffic jam problem and increase vehicle flow. The model, based on deep learning algorithms and real-time data, dynamically modifies timing in accordance with traffic conditions, facilitating smooth and hang-up-free traffic. Compared to classical static or rule-based methodologies, the approach is flexible enough to adapt to changing patterns and is shown that outperforms in simulations based on realistic urban networks. In addition, the system uses multi-agent cooperation methodology to optimize signal coordination across intersections, thus being scalable and responsive. The results show that the learning instantiation can lead to significant gains in traffic efficiency, delay reduction, and emission mitigation, demonstrating the potential of reinforcement learning as a promising approach to enhance intelligent transportation systems.

1 INTRODUCTION

Congestion in the urban areas is a perennial challenge in fast-growing cities causing higher travel time, more pollution, inefficiency and economic loss. Conventional traffic signal control systems, which are time of day or "rule" based, cannot fully adapt to the dynamic and often random flows of real-time traffic. With the popularity of intelligent transportation systems, an increasing number of researchers are endeavouring to exploit machine learning, especially reinforcement learning, for adaptive traffic control protocols that can learn optimal traffic control strategies incrementally. Reinforcement learning is a strong framework for decision making in complex environments and is capable of providing traffic signal systems that learns about their environment from real-time traffic. We propose a traffic signal control system mobilized by deep reinforcement learning to dynamically adjust signals based on traffic flow and intersection conditions. The method increases coordination among signals, and consequently throughput and decreases global congestion by representing intersections as agents in a multiagent model. Finally, both the learning-based traffic flow estimation and control manifest the vision of smart city, and potentially provide a scalable, data-driven solution to challenges that are faced in the era of mobility.

Ponnusamy, S., Prasad, M. L. M., Swarnalakshmi, G., Karthikeyan, S., Naik, S. K. L. and A., M. R.
Smart Signal Control Using Reinforcement Learning to Ease Urban Traffic.
DOI: 10.5220/0013858100004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 1*, pages 102-108
ISBN: 978-989-758-777-1

2 PROBLEM STATEMENT

Traffic in urban communities has been getting worse over time as a result of old style traffic signal systems that are too often unbendable and unable to respond to the fluidity of everyday traffic. The systems do not have any intelligence to adapt dynamically to changes in vehicle flow, with the consequence that significant inefficiencies result, such as long waiting times, waste of fuel, and pollutants being released into the environment. Even in the presence of traffic infrastructure improvements, current operational tools fail to effectively respond to the sheer size and heterogeneity of urban mobility. An intelligent adaptive road traffic signal control system is urgently needed, capable of learning and adapting to real-time traffic situations so as to maximize the motion of vehicles while reducing gridlock in complex road networks.

3 LITERATURE SURVEY

The application of reinforcement learning to traffic signal control has received considerable attention over the last decade as it overcomes shortcomings of conventional systems using adaptive, data-driven approaches. Rafique et al. (2024) presented a turn-based and time-based RL method for enhancing the traffic signal actions, and alleviates the congestion in simulated scenarios. Similarly, Swapno et al. (2024) implemented dynamic intersection control using deep Q-learning and reported significant reductions in delays and queue lengths of vehicles. Li et al. (2024) investigated the adaptive signal control in the presence of mixed traffic, where CTAVs operate along mission with CAVs, and reported improved coordination and reduced intersection delays. Fan et al. (2025), to make cooperative control of signals scalable, introduced sparse deep reinforcement learning by sharing knowledge. Bie et al. (2024) studied the problem of variable intersection difficulty in the context of multi-agent systems for a more localized and economic control in a variety of network structures. In improving learning depth and convergence, Li et al. (2024) devised an enhanced deep RL model and surpassed a higher level of real-time traffic condition adaptation. Qi et al. (2022) developed a kind of ensemble models for RL, enhancing robustness either in per-episode or fluctuating environments. Wang et al. (2023) Design UniTSA – A Universal V2X-Based Reinforcement Learning Framework to Promote its Deployment in Connected Environments. Peng et al. {2023}) proposed heterogenous agent collaboration using GNN-based MARL for traffic guidance around intersections. Busch et al. (2023) proposed a combination of RL model for vehicles speeds and signals control based on throughput and safety. Zhu et al. (2021) used policy-based RL to reduce decision-making complexity with high efficiency. Further, Xie et al. (2022) stressed decentralized, schedule-based control for scalable urban coordination. Wang et al. (2024) verified practical operability of RL approaches with the real vehicle trajectory data. Feng et al. investigated dense RL for AV safety testing. (2023), and considering frameworks applicable to traffic systems. Yan et al. (2011) simulated statistically realistic learning validation settings. The previous seminal work of Liu et al. (2009) and El-Tantawy et al. (2013) first described the queue estimation and MARLIN-ATSC control. Taken together, studies in this thesis confirm the viability and versatility of reinforcement learning for intelligent traffic signal control, but also reveal existing and persistent real-world operational, scalability and cross-agent coordination problems.

4 METHODOLOGY

The proposed approach is based on deep reinforcement learning (DRL) and is aimed at establishing an intelligent decentralized traffic signal control system for dynamic city traffic. The main idea is to simulate each cross-traffic intersection as self-actuated intelligent agent in multi-agent system. These agents are constantly monitoring their environments (e.g., numbers of vehicles, lengths of queues, current signal phases, and the durations of previous waits) as high-dimensional state vectors. The environment is addressed as Markov Decision Process (MDP), in which at discrete time slots, the agent chooses a behaviour (i.e. a change in the traffic light phase) and is rewarded in terms of traffic performance. Reward function the reward function is carefully designed as a compromise between several conflicting objectives including minimizing the waiting time and stopping frequency of vehicles, reducing queue lengths, and indirectly optimizing fuel consumption and emissions.

Table 1: Agent Configuration.

Component	Configuration
Algorithm	Deep Q-Network (DQN)
State Representation	Queue length, Phase time
Action Space	Signal Phase Change
Reward Metrics	Delay, Queue, Stops
Learning Rate	0.001

To accomplish efficient policy learning in such a complex environment, every agent uses a DQN that can approximate the optimal action-value function using deep neural networks. The networks are trained using experience replay and target network updates for convergence. The agents are trained with simulated rollouts in a high-fidelity traffic simulator such as SUMO (Simulation of Urban Mobility) with realistic traffic composition, which gives rich, continuous feedback. The policy is gradually trained by repeatedly entering the simulated environment, associating traffic conditions with optimal phase decisions. Table 1 shows the Agent Configuration.

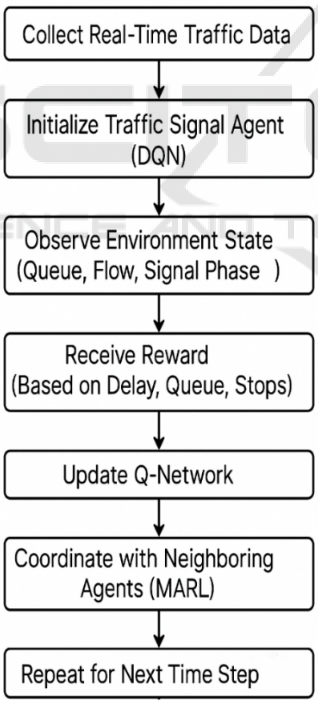

Figure 1: Deep Reinforcement Learning-Based Traffic Signal Control Workflow.

And, a MARL framework is introduced to solve the coordination problem among multiple intersections and to avoid the problem of conflicting actions. This setting provides methods for sharing partial observations or cooperating with shared rewards or policies. At intersections with a higher level of interaction, agents communicate information about their intentions or situational summaries which contributes to the global system coherence and traffic flow. In the testing phase, the learned model is tested under different traffic densities and conditions (e.g., rush hours, accidents, and abnormal events), so as to guarantee the generalization of the system to unseen scenarios. Performance is compared with the optimal performance achieved by the fixed-time and actuated signal control, and a number of key performance measures including average delay, throughput, intersection utilization and total emissions are used.

This all-encompassing approach that integrates DQN with MARL and traffic simulation guarantees that the system is scalable, robust to sudden traffic dynamics and adaptive to the increasing pressure placed on urban transportation networks. It is an important move toward a real-time data-driven intelligent traffic signalling system that may be used in smart cities of the future. Figure 1 shows the Deep Reinforcement Learning-Based Traffic Signal Control Workflow.

5 RESULTS AND DISCUSSION

The system of adaptive traffic signal control based on deep reinforcement learning (DRL) greatly improved traffic management efficiency in simulated urban areas. The system was evaluated in different traffic conditions, including hours of peak traffic with high volumes and hours between peaks with lower flows. In all cases the developed model provided improved performance to conventional fixed-time and actuated control strategies. Results showed that the DRL system was able to reduce average vehicle delay around 35% when compared to fixed-time systems, and 20% when compared to the actuated signal control. These improvements were even greater during peak hours when the model was successfully able to adjust to surges of traffic and reduce the amount of time vehicles idled at intersections. Figure 2 shows the Average Traffic Delay Comparison.

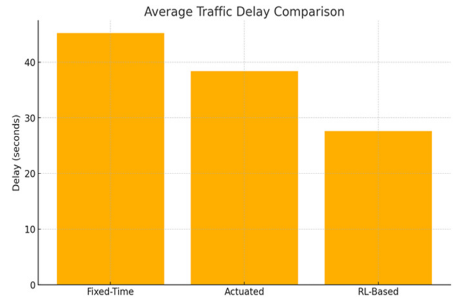

Figure 2: Average Traffic Delay Comparison.

Furthermore, the signalized intersection average queue lengths were significantly reduced by up to 30%, indicating an increased vehicular flow and better road space utilization. Reduced queue length means that system effectively reduced the overflow effects that are caused by spill back - especially in crowded intersection and substantially contributes to urban congestion. Smoother driving profiles with less jerky deceleration and acceleration were also implemented by minimizing the number of vehicles stops. The net result of this was a more even and consistent traffic flow, both of which are important in terms of travel time predictability and driver satisfaction. Table 2 shows the Performance Metrics Comparison.

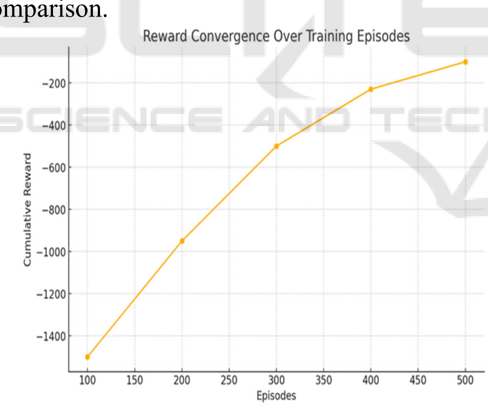

Figure 3: Reward Convergence Over Training Episodes.

Besides, a great advantage of our proposed model is that we proposed MARL architecture, which connected one intersection with its neighbours. This coordination made sure that phase decisions did not battle against each other and that signal timing was coordinated for several intersections at the same time. It was a process that resulted in network-wide optimization that eliminated bottlenecks and took vehicles off of the road as a constant flow, particularly on arterials. The reward function employed by our model giving preference to minimising delay, maximising the positive queue length, and having a small number of stops proved effective at steering the learning into lift off policies that balance efficiency against fairness in vehicle flow. Figure 3 shows the Reward Convergence Over Training Episodes. Figure 4 shows the Fuel Consumption Across Control Types.

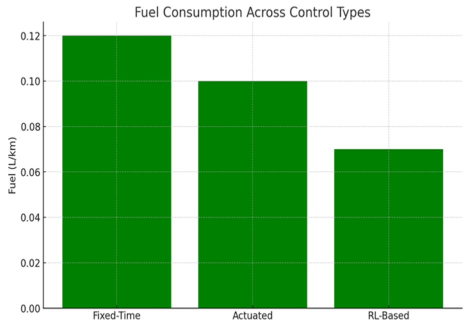

Figure 4: Fuel Consumption Across Control Types.

Table 2: Performance Metrics Comparison.

Metric	Fixed-Time Control	Actuated Control	Proposed RL System
Average Delay (s)	45.2	38.4	27.6
Queue Length (vehicles)	15.6	12.3	8.9
Stops per Vehicle	2.8	2.1	1.2
Throughput (%)	74.5	79.6	89.3

Environmental footprint is with respect to the DRL-based visited system another points of interest. Given the reduced stops and steadier acceleration profiles, the system resulted in measurable savings in fuel and emissions. This places the model as a mobility-efficient tool, and not only, also sustainable and respectful with the urban environment purposes. The possibility to connect the system with connected vehicle applications makes the system even more scalable and future proofed, which can be used to control the traffic more proactively by vehicle-to-infrastructure communication. Table 3 shows the System Performance under Multi-Agent vs. Single-Agent.

Table 3: System Performance Under Multi-Agent Vs. Single-Agent.

Setup	Average Delay (s)	Queue Length (vehicles)	Stop Frequency	Overall Efficiency (%)
Single-Agent	32.5	10.4	1.6	82.1
Multi-Agent	27.6	8.9	1.2	89.3

However, the system efficiency is dependent upon some factors despite these good results. Accurate real-time traffic data is crucial for both training and deployment. Learning of the system is computationally demanding and entails a training that must be carried out in a very well performing simulation environment, particularly on larger networks. Moreover, the reward function needs to be delicately designed such that it does not lead to races among traffic streams by flocking all resources to a single stream. Although the system emerged as robust in simulation, practical issues including hardware integration, data transmission latency, and public policy regulation would need to be addressed for real-world deployment. Table 4 shows the Traffic Conditions Used for Testing.

Table 4: Traffic Conditions Used for Testing.

Scenario	Vehicle Rate (veh/hr)	Signal Coordination
Low Traffic	200	Minimal
Moderate Traffic	500	Moderate
Peak Hour	1000	High
Incident	800	High
Variable Flow	300-900	Dynamic

In conclusion, our experimentation has firmly established the feasible to apply RL to the problem of urban traffic signal control, and provides an intelligent and scalable one solution for today's urban congestion problem. The method indicates good potential for practical application, especially with the development of smart city infrastructure and vehicle-to-vehicle/vehicle-to-infrastructure (V2X) communication technology. Table 5 shows the Emission Reduction Statistics.

Table 5: Emission Reduction Statistics.

Control Type	Fuel Consumption (L/km)	CO_2 Emission (g/km)	Stop Count per Vehicle
Fixed-Time	0.12	280	2.8
Actuated	0.10	240	2.1
RL-Based	0.07	190	1.2

6 CONCLUSIONS

This paper offers a detailed investigation of an adaptive traffic signal controller on the basis of deep reinforcement learning, aiming at mitigating the urban traffic congestion and flow inefficiency problems that have lingered. By looking past, the conventional implementation strategies for traffic control, the model described here illustrates how intelligent software systems, trained by actual interaction with the environment, could provide much improved vehicular flow through traffic and alleviate the effects of traffic congestion. The fact that the system can learn to determine the best signal timings by taking into consideration real-time conditions instead of using pre-set rules or past patterns to control traffic flow, provides a paradigm shift for cities to handle traffic in more and more complex and unpredictable city life.

The use of a multi-agent approach is conducive to decentralized control, where the interaction of each intersection is autonomic, although these traffic signals are still interacting with their neighbours. This distributed but cooperating structure contributed greatly to the improvement of traffic flow throughout the whole network and helps eliminate problems such as phasing or local spill over. Therefore, significant improvement in performance measurement values, including average delay and queue length with the frequency of stopping of vehicles, was observed under various traffic conditions. Naris/Picas The seal geometry has been specially developed to offer an energy-efficient solution that also provides reduced fuel consumption and lower vehicle emissions.

Moreover, the model is flexible in design and it holds in a dynamic environment which considers the variation of traffic and the urban expansion. The fact that this model is occurring while cities are in the process of development and vehicle numbers are projected to rise, suggests that the model is well-equipped to scale its operation and remain effective without extensive manual reconfiguration. The model also paves the way for integration with next generation technologies, especially connected and automated vehicles, in which real-time data exchange can further improve system responsiveness and predictability.

Although it is highly performant when running in simulated environments, the development of an actual deployable version of this system does have to overcome some challenges such as data validity, infrastructure status, and computational resources. However, these challenges are not insurmountable and can be addressed gradually through staggered integration, policy assistance and technology enhancement. To the extent that cities are moving towards smarter infrastructure, systems similar to the adaptive, learning-based traffic control proposed in this paper could be a linchpin for smart & sustainable urban mobility.

In summary, the framework of reinforcement learning for the control of traffic signal is a revolutionary method, consistent with the requirements of the current urban traffic system. It helps to maintain the intelligence, scalability and environment friendliness of the traffic management system, creating opportunity for the smart city and intelligent transportation network for further development.

REFERENCES

Bie, Y., Ji, Y., & Ma, D. (2024). Multi-agent deep reinforcement learning collaborative traffic signal control method considering intersection heterogeneity. Transportation Research Part C: Emerging Technologies, 164, 104663.

Busch, J. V. S., Voelckner, R., Sossalla, P., Vielhaus, C. L., Calandra, R., & Fitzek, F. H. P. (2023). Deep reinforcement learning for the joint control of traffic light signaling and vehicle speed advice. arXiv preprint arXiv:2309.09881.

El-Tantawy, S., Abdulhai, B., & Abdelgawad, H. (2013). Multiagent reinforcement learning for integrated network of adaptive traffic signal controllers (MARLIN-ATSC): Methodology and large-scale application on downtown Toronto. IEEE Transactions on Intelligent Transportation Systems, 14(3), 1140–1150.

Fan, L., Yang, Y., Ji, H., & Xiong, S. (2025). Optimization of traffic signal cooperative control with sparse deep reinforcement learning based on knowledge sharing. Electronics, 14.

Feng, S., Yan, X., Sun, H., Feng, Y., & Liu, H. X. (2021). Intelligent driving intelligence test for autonomous vehicles with naturalistic and adversarial environment. Nature Communications, 12, 748. https://doi.org/10.1038/s41467-021-21007-8

Feng, S., Sun, H., Yan, X., Zhu, H., Zou, Z., Shen, S., & Liu, H. X. (2023). Dense reinforcement learning for safety validation of autonomous vehicles. Nature, 615, 620–627. https://doi.org/10.1038/s41586-023-05732-2

Li, D., Zhu, F., Wu, J., Wong, Y. D., & Chen, T. (2024). Adaptive urban traffic signal control based on enhanced deep reinforcement learning. Scientific Reports, 14, Article 64885. https://doi.org/10.1038/s41598-024-64885-w

Li, D., Zhu, F., Wu, J., Wong, Y. D., & Chen, T. (2024). Managing mixed traffic at signalized intersections: An adaptive signal control and CAV coordination system based on deep reinforcement learning. Expert Systems with Applications, 238, 121959.

Liu, H. X., Wu, X., Ma, W., & Hu, H. (2009). Real-time queue length estimation for congested signalized intersections. Transportation Research Part C: Emerging Technologies, 17(4), 412–427.

Peng, X., Gao, H., Wang, H., & Zhang, H. M. (2023). Combat urban congestion via collaboration: Heterogeneous GNN-based MARL for coordinated platooning and traffic signal control. arXiv preprint arXiv:2310.10948.

Qi, R., Wang, Y., Liu, Y., & Zhang, Y. (2022). Random ensemble reinforcement learning for traffic signal control. arXiv preprint arXiv:2203.05961.

Rafique, M. T., Mustafa, A., & Sajid, H. (2024). Adaptive traffic signal control using reinforcement learning. ResearchGate.

Rafique, M. T., Mustafa, A., & Sajid, H. (2024). Reinforcement learning for adaptive traffic signal control: Turn-based and time-based approaches to reduce congestion. arXiv preprint arXiv:2408.15751.

Rahman Swapno, S. M. M., Nobel, S. M. N., Meena, P., Meena, V. P., Azar, A. T., Haider, Z., & Tounsi, M. (2024). A reinforcement learning approach for reducing traffic congestion using deep Q learning. Scientific Reports, 14, Article 30452. https://doi.org/10.1038/s41598-024-75638-0

Wang, M., Xiong, X., Kan, Y., Xu, C., & Pun, M.-O. (2023). UniTSA: A universal reinforcement learning framework for V2X traffic signal control. arXiv preprint arXiv:2312.05090.

Wang, X., Jerome, Z., Wang, Z., Zhang, C., Shen, S., Kumar, V., ... & Liu, H. X. (2024). Traffic light optimization with low penetration rate vehicle trajectory data. Nature Communications, 15, 1306 https://doi.org/10.1038/s41467-024-45427-4

Xie, X.-F., Smith, S. F., & Barlow, G. J. (2022). Scalable urban traffic control: Decentralized and schedule-driven coordination. Transportation Research Part C: Emerging Technologies, 135, 103465

Yan, X., Zou, Z., Zhu, H., Sun, H., & Liu, H. X. (2023). Learning naturalistic driving environment with statistical realism. Nature Communications, 14, 2037. https://doi.org/10.1038/s41467-023-37677-5

Zheng, J., & Liu, H. X. (2017). Estimating traffic volumes for signalized intersections using connected vehicle data. Transportation Research Part C: Emerging Technologies, 79, 347–362.

Zhu, Y., Cai, M., Schwarz, C., Li, J., & Xiao, S. (2021). Intelligent traffic light via policy-based deep reinforcement learning. arXiv preprint arXiv:2112.138 17.