

Traffic flow optimization using reinforcement and thread-based V2X communication for smart traffic management

Parul Arora¹, Ritika Wason¹, Devansh Arora², M. N. Hoda¹, Sumit Gupta³

¹Department of Computer Science and Applications, Bharati Vidyapeeth's Institute of Computer Applications and Management, Delhi, India

²Department of Artificial Intelligence, Sprinklr, Bengaluru, India

³Department of Research and Development, Xsys Software Technologies, Bengaluru, India

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ABSTRACT

This research proposes an advanced framework that integrates reinforcement learning techniques with thread-based vehicle-to-everything (V2X) communication protocol to address urban traffic jams, which lead to increased delay, inefficient fuel consumption, and deteriorating air quality, posing a significant challenge to sustainable living. This framework empowers cars to “talk” directly to each other as well as with traffic signals, adapting to the real-time flow on the roads. By placing the decision-making process closer to where it’s needed, right at the network’s edge, the system is able to respond quickly to changes in traffic without relying on the usual pre-set signal cycles. Unlike many traditional traffic management solutions that are slow to adjust, the proposed framework allows vehicles and intersections to coordinate in real time. This reduces unnecessary waiting, smooths out traffic flow, and helps cut down on emissions. Through detailed simulations using the simulation of urban mobility (SUMO) traffic model, it was found that this system led to significant improvements: average waiting time was reduced by over 40%, queue lengths were cut by more than half, and vehicle throughput increased by nearly 30%. Additionally, fuel consumption dropped by approximately 24%, and carbon dioxide (CO₂) emissions were reduced by more than 25% compared to existing systems.

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Corresponding Author:

Sumit Gupta

Department of Research and Development, Xsys Software Technologies

Bengaluru, India

Email: sumit@xsyssoftwaretechnologies.com

1. INTRODUCTION

Roadway capacity in urban areas hasn't been keeping up with the number of vehicles, and the resulting congestion takes a toll on commuter time and city budgets [1]. Much of the blame is due to fixed-time signals. Tuned once and left alone, there is a cycle: queues, wasted fuel, and stop-start pollution [2] that takes place, be it a road with traffic or one with none. Centralized control rooms are fine as long as they can be covered, but a rapidly growing city is too far ahead both in extent and in response [3].

Another option is to delay the decision until the intersection, even within the vehicles, and this is the task this work tries to accomplish. The adaptive part is from reinforcement learning, which optimises its signal selection as it observes traffic for longer, whilst the communication part is based on the wireless standard thread [4] designed for the internet of things (IoT) which provides fast, reliable, low-energy communications between vehicles and road-side units [5]. No central authority is involved anywhere, as vehicles and roadside units (RSUs) negotiate to gain access to intersections [6]. Processing remains at the edge, next to the data source,

allowing for almost real-time reaction and the benefit to land on delay, fuel and emissions all at once [7], [8]. The design doesn't require special infrastructure either – the smart-city hardware that is being deployed in many municipalities is sufficient [9]. This has been the direction of IoT networking and edge processing for some time, it was the direction of traffic flow, and it was the direction of road safety [10], [11]. The addition consists of a combination of the virtual traffic light (VTL) concept, thread message, and a learning controller that adjusts itself during run time [12]. The combination achieved 30% greater traffic under realistic simulation of urban mobility (SUMO) loads while using about 25% less fuel.

The use of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication in city-traffic is a long history. Khodabakhshloo and Fatehi [8] were responsible for VTLs, in which vehicles co-ordinating with each other beat today's traffic light system, and Ferreira and d'Orey [13] then converted carbon savings into figures. In an adaptive approach, Nicolosi *et al.* [6] developed a signal scheme based on an IoT concept and won easily over fixed cycles. Meanwhile, thread has established a reputation in the IoT world for its economical power consumption and easy scalability [14] and its high-rate and reliable exchange in smart city environments was demonstrated [1]. Domínguez and Sanguino [7] used artificial intelligence (AI)-controlled signals to ease congestion in dense areas, while Alam's [9] analysis of vehicle-to-everything (V2X) protocols showed that energy is the better metric for real-time traffic messaging, this time for the thread protocol.

There are several other lines of related work, such as smart parking [10] using deep learning, reducing latency and energy required for urban mobility networks [11], and SUMO-supported evidence [12] that VTLs reduce pressure at intersections. Choudhary *et al.* [15] demonstrated edge-managed VTLs without any central controller. All of them are missing one frame that holds reinforcement learning decisions, thread V2X messaging and edge computing in one, and that is what these paper focuses on. The remaining paper is organized as follows: section 2 presents the related work in metode. Section 3 discusses the results and provides a detailed analysis. Section 4 concludes the study and outlines future scope.

2. METHOD

Reinforcement learning and thread-based V2X links are the two pillars of the hybrid traffic flow optimization (HTFO) system, which handles V2V and V2I exchange alike [16]. Put briefly, signals should answer to the road rather than the clock, and live data plus learned decision rules are pointed at the usual troubles: congestion, long waits, and wasted fuel [17]. Speed, position and locally visible congestion go out from every car over thread, a protocol built for quick exchanges on very little power [18]. Nothing travels far; the number-crunching happens at the intersection, so responses stay quick and no remote server is leaned on [19]. An reinforcement learning policy, trained on flows past and present, decides whether a VTL needs to come on at all, and idling time and fuel burn drop as a result [20].

2.1. System architecture

The basic architecture of the system is depicted in Figure 1. As illustrated, the system stacks four layers in its design [18], [19]. All four core layers are described in the figure.

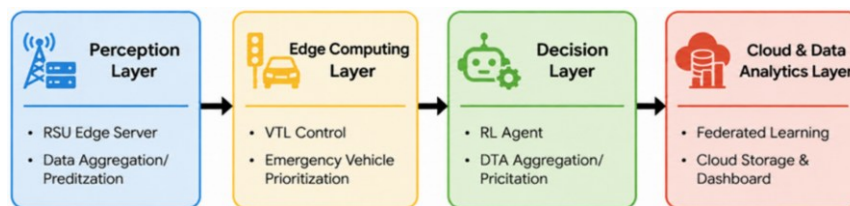


Figure 1. Layered architecture of the proposed system

2.1.1. Perception layer

Data gathering lives at this layer of the proposed architecture. Cars and RSUs are equipped with sensors, GPS, and onboard units that record speed, position, and road occupancy [5]. Thread V2X then circulates these readings quickly, efficiently, and without relying on a central relay.

2.1.2. Edge computing layer

Computation sits by the roadside here [21]. The busier junctions get their readings handled on the spot by RSUs, a prediction module flags where flow is thickening [19]. The reinforcement learning agent raises or drops VTLs as the moment demands [12].

2.1.3. Decision layer

In this layer, it is decided which control actions are taken. The VTL is only activated when traffic requires it, avoiding unnecessary delays [22]. Live predictions divide up the green time, and the standing rules route ambulances through first, with the heavier routes getting extra green [23].

2.1.4. Cloud and data analytics layer

The long-term record is stored in the cloud. Federated learning then merges together what the models at different intersections have learned. City personnel can monitor the entire network on a dashboard, when necessary, they can step in to help.

2.2. Hybrid traffic flow optimization: a mathematical model

In the HTFO model, there are only three costs: time lost at red, standing queue, and energy spent. Each signal decision is evaluated based on the traffic that is actually present. These models are explained through mathematical modelling in sections as follows.

2.2.1. Traffic flow optimization model

Simple accounting opens the model. Arrivals beyond departures lengthen a queue; the reverse shortens it. That is flow conservation of (1).

$$A_j - D_j = \frac{dL_j}{dt} \quad (1)$$

Where A_j denotes arrivals at the intersection j , D_j departures, and L_j the queue standing there. The quantity minimized is waiting time summed across intersections, as in (2).

$$\text{Minimize } \sum \tau_j \quad (2)$$

Queues are never allowed to run away, as in (3).

$$L_j \leq L_{\max} \quad (3)$$

2.2.2. AI-driven reinforcement learning model

Every intersection is its own agent. It watches four things: the standing queue (L_j), vehicle speeds (v_i), link quality toward cars and infrastructure (g_{ij}), and the transmit power in use at each vehicle (p_i). Four moves are open to it: switch the signal, hold it, or raise or drop a VTL. Reward climbs as waiting time, queue length, or energy spend falls, as formulated in (4); here, the weights μ , ν and ξ set the relative priorities.

$$R_t = -(\mu \sum \tau_j + \nu \sum L_j + \xi \sum p_j) \quad (4)$$

Deep Q-learning handles the training and replayed experience the sharpening of the policy.

2.2.3. Energy-efficient thread-based communication model

Radio energy gets its own treatment [11]. A vehicle transmits no harder than its distance from the intersection requires, in place of any fixed level, as in (5).

$$p_i = p_{\min} + \eta(1 - \frac{r_{ij}}{r_{\max}}) \quad (5)$$

In which $p_{\min}$ is the floor power, η a tuning constant, r_{ij} the vehicle-to-intersection distance, and $r_{\max}$ the reach of the communication range.

2.3. Flow of the proposed algorithm

Vehicles sensing congestion are what start a cycle. Their speed and position reports reach nearby RSUs over thread, one channel carrying V2V and V2I alike [15]. The RSU adds hardly any relay delay [24]. At the edge, machines by the intersection then take stock, counting vehicles, gauging speeds, watching the queue grow, and no server round trip enters into it [22]. From that picture, the AI fixes the signal plan [23]; VTLs rise or fall, and vehicles get through with fewer halts [25].

2.4. Experimental, mathematical, and simulation modelling

Synthetic traffic now exercises the model inside SUMO, with static signal control serving as the baseline for the proposed traffic flow optimization (TFO) framework. Every experiment is conducted in

SUMO. OpenStreetMap (OSM) data for a mid-sized city gave the road network its interconnected junctions, signalized crossings, and two-way streets; Figure 2 shows the layout with its dominant flows.

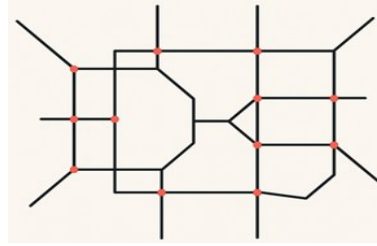


Figure 2. Road network used in the simulation

2.4.1. Data generation

Repeatability is why the demand is synthetic. Several intersections received generated traffic whose arrival rates, queue lengths and vehicle mix, emergency vehicles among them, changed slot by slot across peak and off-peak periods. Parameter values, the queue capacity (L_{max}), the minimum transmit power (p_{min}) and the reward weights (μ, v, ξ), were fixed from the literature and from practical urban limits. Table 1 carries the figures for each 15-minute slot.

Table 1. Synthetic traffic demand used in the runs

Intersection	Time slot	Vehicle arrivals (cars/hr)	Emergency vehicles (per hr)	Buses (per hr)	L_{max} (max queue)
A	8–9 AM	280	6	20	25
A	9–10 AM	320	8	18	30
B	8–9 AM	210	3	12	20
B	9–10 AM	240	5	10	22
C	8–9 AM	195	4	9	18
C	9–10 AM	225	5	11	21

2.4.2. Application of the mathematical model

Each simulation timestep works through the following:

- i) Traffic flow optimization
 - Arrivals (A_j) and departures (D_j) are tallied at every intersection, the queue updating as (6).

$$L_j(t+1) = L_j(t) + A_j - D_j \quad (6)$$

- Waiting time τ_j comes out of the queue dynamics and service rates.
- A queue saturates at L_{max} , as a real road would.
- ii) Reinforcement learning control: one reinforcement learning agent serves each intersection. State: [queue L_j , mean speed v_i , link quality g_{ij} , transmit power p_i]; actions: {switch signal, hold, VTL on/off}. The reward is that of (4), and deep Q-learning lifts the policy over simulated episodes.
- iii) Thread-based V2X energy control: transmit power per vehicle follows (5) ($p_{min} = 0.5$ W, $\eta = 2$, $r_{max} = 250$ m; r_{ij} read live).

3. RESULTS AND DISCUSSION

The entire HTFO stack was transported by SUMO, synthetic demand was injected via queue logic, and reinforcement learning signal control was used to control the simulator, which was steered by the traffic control interface (TraCI). The two hours of the morning rush are replayed in each run, and trajectories, signal states, queue lengths, waiting times, vehicles served, as well as fuel and emissions per vehicle, are recorded for every step. The SUMO floating car data (FCD) output, whose data is the source of Figure 3, shows the movement of vehicles within the network at peak hour; congestion pockets, favoured routes or bottlenecks in the making are all discernible. There was no way that the phases remained constant. Demand fluctuated around, and it was the lengthening and shortening of reds and greens (plus the quieter hours) that were remembered by Figure 4.

Most of this gain is provided by timing adaptation. As expected from an agent that cannot handle local congestion, the reinforcement learning agent continuously adapted green durations in every RSU equipped

with a thread node to the current level of congestion. Figure 5 compares the two at a major intersection: adaptive phases catch up to the traffic, the static phases are at ground level, and the moving version is at the end of the waits and throughput. This was observed by Nicolosi *et al.* [6] for the IoT-based adaptive control. A heatmap of the delay with the edge outputs (Figure 6) shows where the delay will actually occur. The cells with red and orange are the points where they will collect, blue marks the points where they will run free, and the hottest cells name the intersections that are most in need of attention at peak.

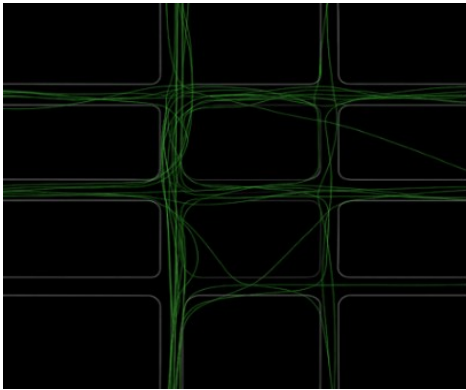


Figure 3. Vehicle traces at the prime junctions during a typical rush hour

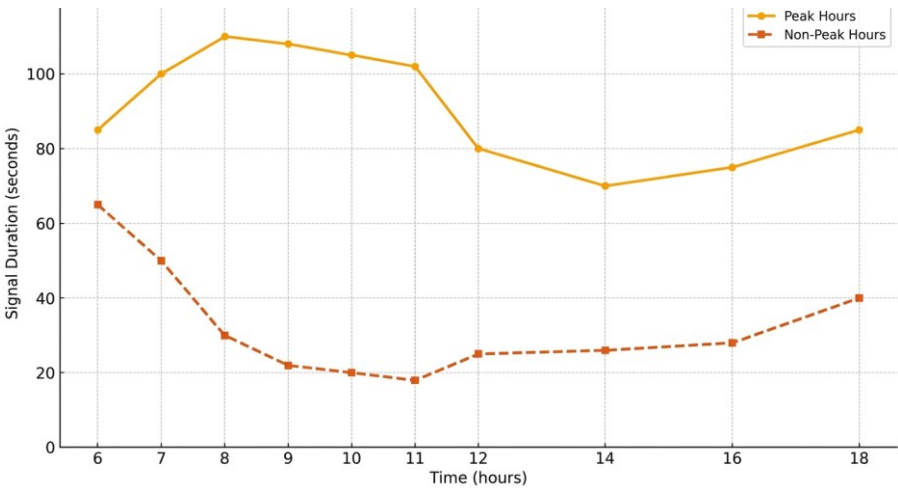


Figure 4. Signal timing adjustments over the test period

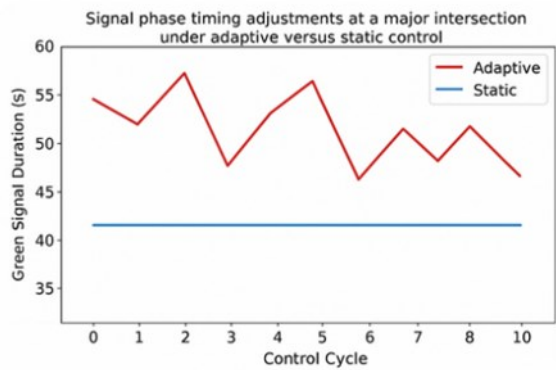


Figure 5. Adaptive versus static phase timings at one major intersection

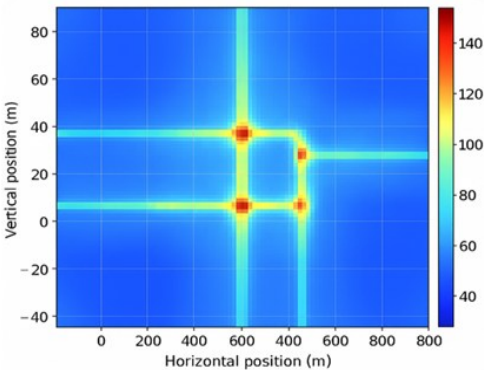


Figure 6. Average vehicle waiting times across the network at peak hour

The environmental impact is borne by fuel. For the four main intersections, they were metered using fixed cycles and with reinforcement learning + thread control, with the latter using between 18% and 25% less, depending on the intersection, due primarily to the reduction of idling and the improvement of flow. The readings show that a similar fuel and emission reduction was achieved by VTL control [13].

If the fuel is burned in the atmosphere, then the carbon dioxide (CO_2) is consumed. Figure 7 shows four peak hour periods, during which the reinforcement learning + thread system produces lower emissions than those of static control, in each of which, the same reductions are observed as in Lv and Shang [11] survey for intelligent transportation systems. The results of queue length at two intersections during one simulation cycle and CO_2 emissions under adaptive and static control are shown in Figures 8 and 9, respectively. Figure 8 shows the queue length at two intersections during one simulation cycle while Figure 9 shows the CO_2 emissions under adaptive and static control.

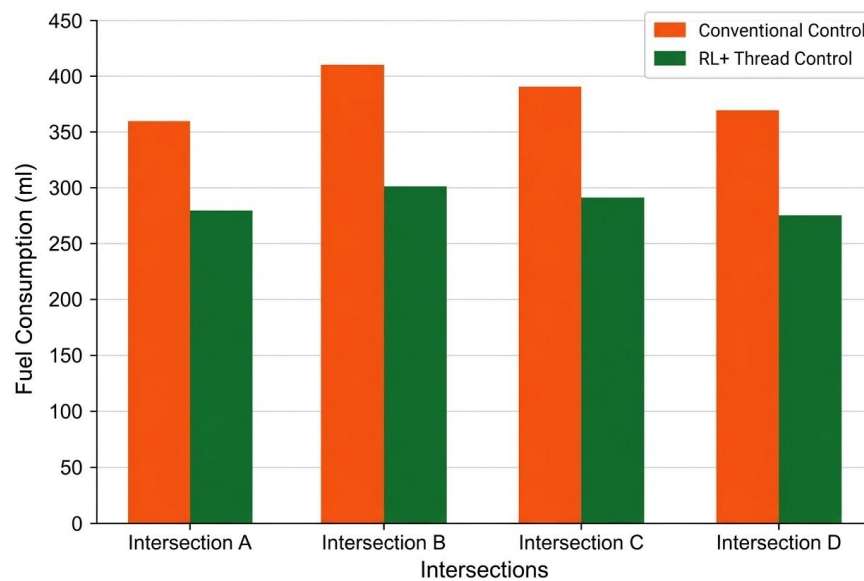


Figure 7. Total fuel consumption, fixed cycles versus reinforcement learning + thread

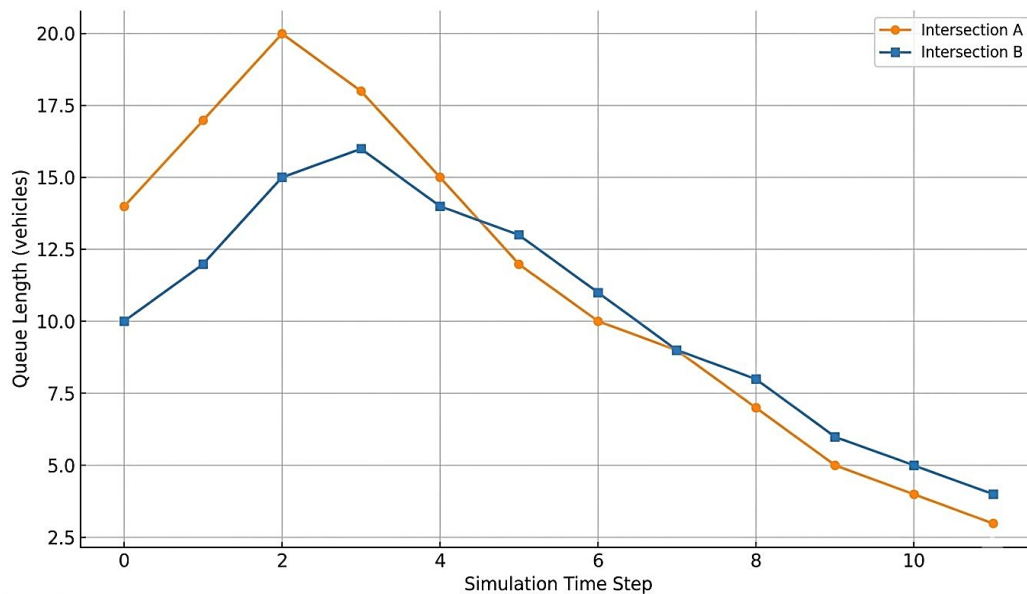
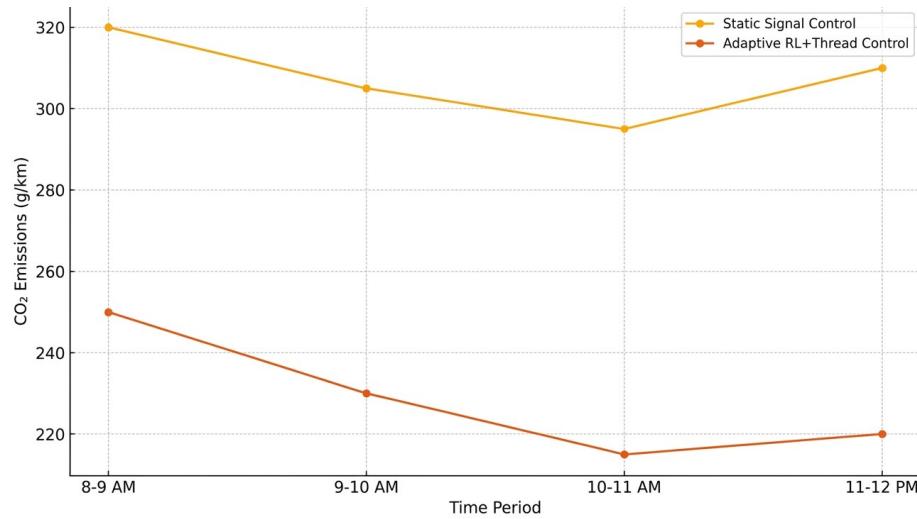


Figure 8. Queue lengths at two intersections across one simulation cycle

Figure 9. CO₂ emissions under adaptive and static control

The key findings are presented in Table 2. The mean wait times were reduced from 65 s to 38 s compared to baseline and to worst queue, while the hourly throughput was increased from 810 to 1040 vehicles. Fuel eased from 25.3 to 19.2 L/hr, CO₂ from 78,400 to 58,700 g/hr. The improvement is evident on either measure, operational, or environmental.

Table 2. Performance of HTFO against the baseline

Metric	Baseline control	HTFO (proposed)
Avg. waiting time (sec)	65	38
Max queue length (veh)	29	13
Vehicles serviced/hour	810	1040
Fuel consumption (L/hr)	25.3	19.2
CO ₂ emissions (g/hr)	78,400	58,700

To place these results in context, Table 3 compares HTFO with recent reinforcement learning-based traffic control studies reported between 2024 and 2026. Hu and Li [26] coordinated multiple intersections through a multi-agent double deep Q-network and reported reductions of about 40% to 60% in both waiting time and queue length over pre-timed control. Cai and Wei [27] strengthened a dueling double deep Q-network with prioritized experience replay and noisy networks, cutting average waiting time by 60.9% and average queue length by 39.5% against fixed-time control in SUMO. Nghiem *et al.* [28] jointly optimized signal phases and the trajectories of cooperative connected and autonomous vehicles with a soft actor-critic agent, reducing average waiting time by up to 80% under high-demand scenarios. These studies, however, restrict their objectives to signal timing or vehicle trajectories and do not report the energy or environmental footprint of the control loop. HTFO achieves a comparable operational gain, with 41.5% lower waiting time, a 55.2% smaller peak queue, and 28.4% higher throughput, while additionally budgeting the V2X radio power through thread and converting the smoother flow into measured savings of 24.1% in fuel and 25.1% in CO₂ emissions.

Table 3. Comparison of HTFO with recent reinforcement learning-based traffic control studies

Study	Approach	Waiting time reduction	Queue length reduction	Fuel/CO ₂ reduction
Hu and Li [26]	Multi-agent double deep Q-network signal coordination	40-60%	40-60%	Not reported
Cai and Wei [27]	Enhanced dueling double deep Q-network (PN_D3QN)	60.9%	39.5%	Not reported
Nghiem <i>et al.</i> [28]	Soft actor-critic with cooperative connected autonomous vehicles	Up to 80%	Not reported	Not reported
HTFO (this work)	Reinforcement learning with thread-based V2X and edge computing	41.5%	55.2%	24.1% / 25.1%

4. CONCLUSION

This paper introduces the basis of a scalable and flexible traffic control concept, thus heralding a new era of sustainable urban mobility. This study saw significant improvements with our tests carried out on SUMO: cars drove more efficiently, wait times at intersections decreased from 65 s to 38 s and there was a noticeable reduction in fuel consumption (from 25.3 to 19.2 litres per hour) and CO₂ emissions (from 78,400 to 58,700 grams per hour). The maximum number of vehicles in the queue at intersections dwindled from 29 to 13 vehicles and the number of vehicles per hour running increased from 810 to 1,040. This is not just about reducing driver frustration but a positive move towards cleaner cities as well. Smart systems with data and smart algorithms can change the old traffic setups to modern, flexible networks, the study demonstrates. The proposed method was found to be successful both during busy periods and quiet periods, it was shown to be able to cope with the fluctuations in normal urban life. Looking forward, there's a lot of room to enhance on this research in future. Vehicular ad hoc networks (VANETs), and a broader array of IoT sensors, will further speed up and increase the accuracy of data collection. Another possibility for using advanced machine learning is to predict traffic jams before they occur, benefiting both city planners and drivers. The model could also be modified in future to prioritise emergency vehicles, enhance pedestrian safety and take into account the needs of buses, bicycles, and other forms of transport.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Parul Arora	✓	✓	✓	✓		✓	✓	✓	✓		✓		✓	✓
Ritika Wason					✓	✓	✓			✓				✓
Devansh Arora	✓		✓		✓			✓	✓					✓
M. N. Hoda	✓					✓	✓			✓		✓	✓	
Sumit Gupta	✓			✓		✓		✓		✓		✓		

C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

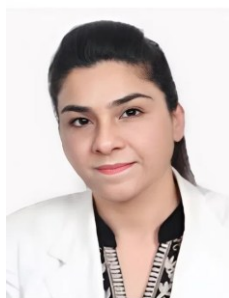
The data that support the findings of this study are available from the corresponding author, [SG], upon reasonable request.

REFERENCES

- [1] M. Soyuturk, K. N. Muhammad, M. N. Avcil, B. Kantarci, and J. Matthews, "From vehicular networks to vehicular clouds in smart cities," in *Smart Cities and Homes: Key Enabling Technologies*, 2016, pp. 149–171, doi: 10.1016/B978-0-12-803454-5.00008-0.
- [2] S. H. Imtiyaz and S. A. M. Sadique, "Intelligent transport systems: a comprehensive way to regulate and curb vehicular pollution," in *2015 International Conference on Communication and Signal Processing, ICCSP 2015*, Nov. 2015, pp. 1230–1235, doi: 10.1109/ICCSP.2015.7322704.
- [3] M. Khanmohamadi and M. Guerrieri, "Advanced sensor technologies in CAVs for traditional and smart road condition monitoring: a review," *Sustainability*, vol. 16, no. 19, Oct. 2024, doi: 10.3390/su16198336.
- [4] G. Shyamala, G. B. Pallavi, N. R. Latha, and I. S. Rajesh, "Coalition-based game-theoretic routing technique for delay-tolerant networks with cost and congestion optimization," *International Journal of Computational Intelligence in Engineering*, vol. 1, no. 1, pp. 16–28, 2026, doi: 10.5281/zenodo.19513313.

- [5] I. S. Rajesh, H. G. Mohan, U. N. Ranjitha, M. S. Krishnamurthy, and C. Maithri, "FLQL-VANET: a hybrid of fuzzy logic and Q-learning schemes for QoS-aware routing in VANET," *International Journal of Intelligent Engineering & Systems*, vol. 17, no. 6, 2024, doi: 10.22266/ijies2024.1231.92.
- [6] V. Nicolosi, M. D'Apuzzo, A. Evangelisti, and M. Augeri, "A new methodological approach for road friction deterioration models development based on energetic road traffic characterization," *Transportation Engineering*, vol. 16, Jun. 2024, doi: 10.1016/j.treng.2024.100251.
- [7] J. M. L. Domínguez and T. J. M. Sanguino, "Review on V2X, I2X, and P2X communications and their applications: a comprehensive analysis over time," *Sensors*, vol. 19, no. 12, Jun. 2019, doi: 10.3390/s19122756.
- [8] M. Khodabakhshloo and A. Fatehi, "Vehicle maneuver evaluation in emergency condition," *Transportation Engineering*, vol. 16, Jun. 2024, doi: 10.1016/j.treng.2024.100230.
- [9] T. Alam, "Data privacy and security in autonomous connected vehicles in smart city environment," *Big Data and Cognitive Computing*, vol. 8, no. 9, Aug. 2024, doi: 10.3390/bdcc8090095.
- [10] G. Ramkumar, "A logical appliance of deep learning methodology for an intelligent parking system for smart cities using internet of things association," in *5th International Conference on Electronics and Sustainable Communication Systems, ICESC 2024*, 2024, pp. 456–463, doi: 10.1109/ICESC60852.2024.10689755.
- [11] Z. Lv and W. Shang, "Impacts of intelligent transportation systems on energy conservation and emission reduction of transport systems: a comprehensive review," *Green Technologies and Sustainability*, vol. 1, no. 1, Jan. 2023, doi: 10.1016/j.grets.2022.100002.
- [12] R. Wason, P. Arora, V. Jain, D. Arora, and M. N. Hoda, "Exploring the convergence of artificial intelligence and mechatronics in autonomous driving," in *Computational Intelligent Techniques in Mechatronics*, Austin, United States: Scrivener Publishing, 2024, pp. 297–316, doi: 10.1002/9781394175437.ch9.
- [13] M. Ferreira and P. M. d'Orey, "On the impact of virtual traffic lights on carbon emissions mitigation," *IEEE Transactions on Intelligent Transportation Systems*, vol. 13, no. 1, pp. 284–295, Mar. 2012, doi: 10.1109/TITS.2011.2169791.
- [14] P. Choudhary, R. K. Dwivedi, and U. Singh, "Open threads-enabled mesh networks in vehicles for real-time traffic monitoring," in *IoT and Cloud Computing Advancements in Vehicular Ad-Hoc Networks*, 2020, pp. 120–143, doi: 10.4018/978-1-7998-2570-8.ch006.
- [15] P. Choudhary, R. K. Dwivedi, and U. Singh, "An analysis of real-time traffic congestion optimisation through VTL in VANETs," *International Journal of Computer Applications in Technology*, vol. 68, no. 1, pp. 12–26, 2022, doi: 10.1504/IJCAT.2022.123232.
- [16] A. Alsaleh, "How do V2V and V2I messages affect the performance of driving smart vehicles?," *Computer Systems Science and Engineering*, vol. 47, no. 2, pp. 2313–2336, 2023, doi: 10.32604/csse.2023.039682.
- [17] Z. Li and E. Peng, "Software-defined optimal computation task scheduling in vehicular edge networking†," *Sensors*, vol. 21, no. 3, pp. 1–13, 2021, doi: 10.3390/s21030955.
- [18] S. Moon and Y. Lim, "Federated deep reinforcement learning based task offloading with power control in vehicular edge computing," *Sensors*, vol. 22, no. 24, 2022, doi: 10.3390/s22249595.
- [19] L. Nkenyerere, S. M. R. Islam, C. A. Kerrache, M. A.-Al-Wadud, and A. Alamri, "Software-defined network-based multi-access edge framework for vehicular networks," *IEEE Access*, vol. 8, pp. 4220–4234, 2020, doi: 10.1109/ACCESS.2019.2962903.
- [20] V. D. Nguyen, T. T. Khanh, N. H. Tran, E. N. Huh, and C. S. Hong, "Joint offloading and IEEE 802.11p-based contention control in vehicular edge computing," *IEEE Wireless Communications Letters*, vol. 9, no. 7, pp. 1014–1018, Jul. 2020, doi: 10.1109/LWC.2020.2978482.
- [21] A. A. Brincat, F. Pacifici, S. Martinaglia, and F. Mazzola, "The internet of things for intelligent transportation systems in real smart cities scenarios," in *IEEE 5th World Forum on Internet of Things, WF-IoT 2019*, Apr. 2019, pp. 128–132, doi: 10.1109/WF-IoT.2019.8767247.
- [22] N. Bermad, S. Zemmoudj, and M. Omar, "Context-aware negotiation, reputation and priority traffic light management protocols for VANET-based smart cities," *Telecommunication Systems*, vol. 72, no. 1, pp. 131–153, 2019, doi: 10.1007/s11235-019-00555-x.
- [23] R. Vani, N. Thendral, J. C. Kavitha, and N. P. G. Bhavani, "Intelligent traffic control system with priority to emergency vehicles," *IOP Conference Series: Materials Science and Engineering*, vol. 455, no. 1, Dec. 2018, doi: 10.1088/1757-899X/455/1/012023.
- [24] F. Al-Turjman and J. P. Lemayian, "Intelligence, security, and vehicular sensor networks in internet of things (IoT)-enabled smart-cities: an overview," *Computers and Electrical Engineering*, vol. 87, Oct. 2020, doi: 10.1016/j.compeleceng.2020.106776.
- [25] J. Liu *et al.*, "Secure intelligent traffic light control using fog computing," *Future Generation Computer Systems*, vol. 78, pp. 817–824, 2018, doi: 10.1016/j.future.2017.02.017.
- [26] T. Y. Hu and Z. Y. Li, "A multi-agent deep reinforcement learning approach for traffic signal coordination," *IET Intelligent Transport Systems*, vol. 18, no. 8, pp. 1428–1444, Aug. 2024, doi: 10.1049/itr2.12521.
- [27] C. Cai and M. Wei, "Adaptive urban traffic signal control based on enhanced deep reinforcement learning," *Scientific Reports*, vol. 14, no. 1, Jun. 2024, doi: 10.1038/s41598-024-64885-w.
- [28] L. D. Nghiem, S. H. Bae, P. M. Thao, and K. K. Yoon, "Enhancing traffic efficiency through deep reinforcement learning-based traffic signal control with cooperative connected and autonomous vehicles," *Applied Sciences*, vol. 16, no. 5, Mar. 2026, doi: 10.3390/app16052576.

BIOGRAPHIES OF AUTHORS



Parul Arora    holds a doctor of Computer Science from Teerthankar Mahaveer University, India in 2017. She is currently a professor at the Department of Computer Science and Applications in Bharati Vidyapeeth's Institute of Computer Applications and Management, Delhi, India. Her research includes intelligent transportation systems, networking, machine learning, graph theory, and operating systems. She is also the advisor for IEE APS Student Chapter at Bharati Vidyapeeth's Institute of Computer Applications and Management. She has published over 30 papers in international journals and conferences. She can be contacted at email: parul.arora@bvica.in or paruldevsum@gmail.com.



Ritika Wason    received her Ph.D. in Computer Science from Sharda University, India in 2015. She is a professor of Computer Science in the Department of Computer Science and Applications in Bharati Vidyapeeth's Institute of Computer Applications and Management, Delhi, India. In addition, she is serving as deputy director. She is also the managing editor for the International Journal of Information Technology (BJIT). She is also a certified Mendeley trainer. Her research interests are in software engineering, machine learning, sustainable systems, agent-oriented systems, and intelligent transportation systems. She can be contacted at email: ritika.wason@bvicam.in or rit2282@yahoo.co.in.



Devansh Arora    holds a bachelor of technology (B.Tech.) in Computer Science and Engineering from Indraprastha Institute of Information Technology. He is currently working as a data scientist with Sprinklr, Gurugram, India. He has many novel applications to his credit published in many journals of repute. His research areas of interest include artificial intelligence and intelligent systems. He can be contacted at email: devanshar202@gmail.com.



Prof. M. N. Hoda    is the founder director of Bharati Vidyapeeth's Institute of Computer Applications and Management, New Delhi (under Guru Gobind Singh Indraprastha University, New Delhi). He has 30 years of vast experience and is an expert member of many board-level committees of Govt. of India, like Department of Science and Technology; Council of Scientific and Industrial Research; and Ministry of Human Resource Development. He is a member of academic council of Guru Gobind Singh Indraprastha University, New Delhi, since 2006. He has also served three terms as the member of board of management and one term as a member of the court of Guru Gobind Singh Indraprastha University, New Delhi. He is also the chairperson for IEEE, Delhi section, and the founder editor-in-chief of International Journal of Information Technology (BJIT), published by Springer Nature. He can be contacted at email: mca.hoda@gmail.com or mca@bvicam.ac.in.



Sumit Gupta    is a seasoned researcher with a strong background in machine learning, deep learning, and AI. He has contributed significantly to the development of intelligent systems and scalable algorithms. His expertise spans cloud computing, networking, computer vision, optimization strategies, and data mining. His work focuses on integrating intelligent data-driven models with high-performance computing platforms, enhancing system efficiency and decision-making capabilities. His interdisciplinary collaboration focuses on exploring innovative applications of ML and AI in fields like healthcare, smart cities, and cybersecurity. Currently, he heads Department of Research and Development, Xsys Software Technologies, Bengaluru. He can be contacted at email: sumit2k4@gmail.com.